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FOREWARD

IEEE CCET SB and Department of EEE, CCET in association with IEEE Kochi Subsection and IEEE Power and Energy Society, Kerala Chapter is organizing IEEE CCET Student Paper Contest 2025(IEEE CCET SPC 2025) on 27th March 2025at Carmel College of Engineering and Technology, Alappuzha. The main objective of this event is to provide a platform for the undergraduate and post graduate students to expose their research idea and receive provisional feedback which shall further enhance their skills and knowledge.

The event includes paper presentation by students on various themes relevant to Electrical & Electronics Engineering, Robotics & Automation and Computer Science& Data Analytics. It was a fulfilling one-day program for candidates to share their knowledge, expertise and experience. Industrial experts and academician from reputed institution were chaired the presentations. Paper presentations oriented towards research and best practices were conducted in two venues. More than 90 papers from interested authors were submitted for the same. However only 43 papers were accepted for the presentation. This publication includes total of 43 full papers that address the topics suggested in the SPC 2025 themes.

Finally, we thank all the presenters for their contribution for IEEE CCET SPC 2025 and Special thanks to Management of Carmel College of Engineering and Technology, IEEE Kochi Subsection and IEEE Power & Energy Society, Kerala Chapter for giving permission to conduct this event. Hope IEEE CCET SPC 2025 have achieved its goals of providing a forum for knowledge exchange, sharing experience in the field of Engineering, maintaining professionalism, fostering strategic networks, and promoting cooperation. We express our gratitude to all committee members, faculty members of our institution who have contributed greatly to make this event a great success.

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Hydrodynamic Performance Analysis of a Stingray-Inspired AUV Using Pressure Contour and Vorticity Simulations

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***Abstract*— Hydrodynamic performance plays a crucial role in the efficiency and manoeuvrability of autonomous underwater vehicles (AUVs), especially those inspired by biological propulsion systems. This study investigates the fluid dynamics of a stingray-inspired AUV, focusing on pressure distribution, vorticity generation, and drag reduction. Unlike traditional propeller-driven systems, stingray-like oscillatory fins generate continuous thrust while minimising turbulence and wake formation. Using Computational Fluid Dynamics (CFD), this research evaluates pressure contour distributions and vortex-shedding effects under varying flow speeds, oscillation frequencies, and turbulence models. The analysis employs k-ω SST, k-ε, and Large Eddy Simulation (LES) turbulence models to compare their effectiveness in capturing unsteady flow interactions. The results reveal that controlled vorticity dynamics significantly reduce hydrodynamic drag, while high-pressure regions along the fin surfaces enhance thrust generation. Additionally, the study highlights how oscillation-induced flow separation affects energy dissipation and propulsion efficiency. The findings contribute to the design optimisation of bioinspired AUVs, offering insights into flow stability, drag minimisation, and energy-efficient underwater locomotion. These results provide a framework for developing next-generation biomimetic AUVs for naval surveillance, underwater exploration, and stealth operations.**

Keywords— Hydrodynamic Performance, Biomimetic Propulsion, Pressure Contours and Vorticity Dynamics.

I. Introduction

The development of autonomous underwater vehicles (AUVs) has significantly evolved due to advancements in biomimetic propulsion systems, which aim to mimic the efficiency of marine species such as stingrays, jellyfish, and fish. Unlike conventional propeller-driven AUVs, which often suffer from high energy consumption, cavitation, and noise signatures, biomimetic propulsion offers greater efficiency, reduced turbulence, and improved stealth capabilities [1]. The ability of stingrays to glide through water with minimal drag and continuous thrust generation makes them an ideal model for designing energy-efficient AUV propulsion systems.

The hydrodynamic efficiency of an AUV is heavily influenced by pressure distribution and vorticity dynamics. Pressure contours reveal how thrust forces are generated along the body and fins of the vehicle, while vorticity simulations illustrate how fluid rotational effects influence drag and stability [2]. Excessive vortex shedding and flow separation can increase energy dissipation and unstable propulsion, reducing overall efficiency [3]. Therefore, accurately assessing pressure gradients and wake structures is crucial for optimising bioinspired propulsion mechanisms.

The application of Computational Fluid Dynamics (CFD) has enabled researchers to study fluid-structure interactions in biomimetic AUVs with high precision. CFD simulations allow for visualising pressure zones, velocity distributions, and vortex formations under different flow speeds and fin oscillation patterns [4]. In this study, we employ k-ω SST, k-ε, and Large Eddy Simulation (LES) turbulence models to analyse the hydrodynamic performance of a stingray-inspired AUV. These models help capture turbulence effects, wake interactions, and boundary layer development, which is essential for evaluating drag reduction strategies.

This research aims to evaluate pressure contour distributions to understand thrust generation and drag effects, analyse vorticity fields to determine how oscillation-induced wake structures impact efficiency, and compare different turbulence models (k-ω SST, k-ε, and LES) for assessing flow stability and energy dissipation. The methodology employed in this study includes a CFD-based hydrodynamic modelling approach, utilising structured meshing, flow parameter variation, and turbulence modelling. The results focus on visualising pressure gradients, velocity fields, and vorticity interactions to provide insights into flow stability and energy-efficient propulsion. The findings will contribute to the design of optimised biomimetic AUVs suitable for underwater exploration, naval defence, and stealth operations.

II. Literature

A. Hydrodynamic Efficiency in Biomimetic AUVs

The study of biologically inspired propulsion has gained significant attention due to its potential to enhance efficiency, manoeuvrability, and stealth in underwater vehicles. Unlike conventional propeller-driven systems, biomimetic AUVs leverage oscillatory or undulatory motion to generate continuous thrust with reduced energy loss [1]. Stingrays, in particular, exhibit a highly efficient swimming

mechanism, where oscillating fin motions generate smooth, fluid interactions, minimising drag and turbulence effects [5]. Previous studies have explored bioinspired propulsion designs, highlighting their superior energy efficiency and lower noise profiles, which are beneficial for naval and underwater reconnaissance applications [2].

B. *Pressure Contours and Their Role in Thrust Generation*

Understanding pressure distribution is critical for optimising biomimetic propulsion systems. High-pressure regions along the fin surfaces generate thrust, while low-pressure zones facilitate fluid acceleration and lift forces [3]. Computational Fluid Dynamics (CFD) studies have shown that optimal fin oscillation frequencies and amplitudes can generate favourable pressure gradients, thereby improving propulsion efficiency [6]. Adaptive control mechanisms have been explored to adjust fin motions dynamically, optimising pressure distribution for varying flow conditions [4].

C. *Vorticity Dynamics and Drag Reduction Strategies*

Vortex shedding and unsteady flow interactions significantly impact the performance of biomimetic AUVs. Uncontrolled vortex formation behind the fins can lead to higher energy dissipation and increased drag, reducing propulsion efficiency [7]. Several numerical and experimental studies have examined vortex control mechanisms, such as active flow manipulation and wake stabilisation strategies, to mitigate drag while maintaining efficient thrust production [8]. CFD-based research indicates that oscillation-induced vorticity can be optimised to create a self-sustaining propulsion loop, allowing the AUV to travel with minimal energy expenditure [9].

D. *Turbulence Modeling in Biomimetic Flow Simulations*

Advanced turbulence models are required to simulate fluid-structure interactions in bioinspired propulsion accurately. The k-ω SST turbulence model has been widely used for predicting boundary layer interactions and wake structures in low-to-medium Reynolds number flows [10]. The k-ε model, while computationally efficient, is less effective in capturing near-wall flow behaviour, making it less suitable for biomimetic applications [11]. Additionally, Large Eddy Simulation (LES) has emerged as a promising tool for analysing unsteady turbulent flows, allowing for detailed visualisation of vortex interactions and energy dissipation effects [12].

E. *Gap in Existing Research and Need for Further Investigation*

Despite significant advancements in biomimetic AUV design and CFD-based performance analysis, several research gaps remain. Existing studies primarily focus on thrust generation and efficiency metrics, with limited emphasis on pressure distribution, vortex formation, and their combined impact on hydrodynamic stability. Moreover, most CFD studies use a single turbulence model, failing to compare multiple modelling techniques to identify the most accurate approach for bioinspired propulsion [13]. This study aims to bridge this gap by comparing different turbulence models (k-ω SST, k-ε, and LES) while evaluating pressure contours and vorticity dynamics in a stingray-inspired AUV.

III. COMPUTATIONAL SIMULATION EXPERIMENTAL SETUP

A. *Methodology*

A Computational Fluid Dynamics (CFD) simulation approach is employed to evaluate the hydrodynamic performance of the stingray-inspired AUV, focusing on pressure distribution, vorticity generation, and drag reduction strategies. The study employs the Navier-Stokes equations to model fluid flow interactions with the oscillating fins. These equations describe the conservation of momentum and mass, ensuring accurate simulation of hydrodynamic forces acting on the AUV. Velocity components, pressure variations, and viscosity effects characterise the fluid flow. The sinusoidal wave function also defines the fin oscillation pattern, where the amplitude, frequency, and phase shift determine the propulsion efficiency.

The hydrodynamic behaviour of the stingray-inspired AUV is governed by the fundamental laws of fluid motion. The incompressible Navier-Stokes equations describe the conservation of mass and momentum, ensuring accurate simulation of fluid flow interactions with the oscillating fins.

The continuity equation is given by:

$$\nabla \cdot u = 0$$

The momentum equation in an incompressible flow is expressed as:

$$\rho\left(\frac{\partial u}{\partial t} + u.\nabla u\right) = -\nabla P + \mu\nabla^2 u + F$$

Where,

ρ is the fluid density.
u is the velocity vector.
P is pressure, μ is the dynamic viscosity.
F represents external forces.

Different turbulence models are tested to accurately capture flow separation, wake formation, and turbulence interactions, including k-ω SST, k-ε, and Large Eddy Simulation (LES). While flow at 0.5 m/s is typically considered laminar based on Reynolds number calculations, the oscillating fins introduce localized turbulence, vortex shedding, and unsteady flow structures. The turbulence models were used to capture these effects, ensuring that the hydrodynamic behaviour remains representative of real-world biomimetic propulsion. The k-ω SST model effectively predicts boundary layer behaviour and vortex interactions, while k-ε is widely used for high-Reynolds number turbulent flows. The LES model provides high-fidelity visualisation of unsteady flow structures, enabling detailed analysis of vortex shedding and energy dissipation effects. The CFD simulations are conducted using Python,

with a pressure-based algorithm for numerical stability and accuracy.

The simulation domain consists of a structured mesh with boundary layer refinement, ensuring accurate capture of fluid-structure interactions near the fins. A grid independence study is performed to optimise the balance between computational cost and solution accuracy. The inlet velocity range of 0.5 m/s to 2.5 m/s was chosen based on typical operating speeds of autonomous underwater vehicles (AUVs). Studies have shown that AUVs designed for reconnaissance and deep-sea exploration generally operate within this velocity range, balancing propulsion efficiency and manoeuvrability. The chosen range ensures that both low-speed cruising and high-speed navigation conditions are considered for a comprehensive hydrodynamic analysis. The AUV is tested under 15 oscillation frequencies and varying Reynolds numbers, enabling a comprehensive study of hydrodynamic stability and energy-efficient propulsion.

B. Computational Fluid Dynamics (CFD) Simulation Setup

The experimentation phase involves evaluating the hydrodynamic performance of the stingray-inspired AUV under varying flow conditions and fin oscillation modes. The primary objective is to understand how pressure distribution, vortex formation, and drag forces influence propulsion efficiency. The CFD model is first validated against existing experimental biomimetic AUV studies, ensuring that numerical predictions align with real-world observations. Convergence studies are performed to confirm the stability of drag and thrust values, ensuring the accuracy of results before full-scale analysis.

Experiments are conducted under low-speed and high-speed flow regimes to analyse the impact of different flow conditions, simulating realistic underwater movement scenarios. The strength of vortex interactions is also varied, allowing for a detailed comparison of oscillation-induced flow separation and wake control strategies. The performance metrics include drag force, lift force, thrust force, vorticity magnitude, and energy efficiency, providing insights into how optimised oscillation patterns influence propulsion effectiveness.

Pressure contour analysis is a key aspect of the study, revealing how thrust is generated and drag is minimised. The results indicate that high-pressure regions near the fin edges contribute to thrust production, while low-pressure areas at the trailing edge reduce fluid resistance. By comparing different turbulence models, it is observed that LES provides the most accurate pressure distribution predictions, capturing fine-scale vortex interactions that influence AUV stability.

Vorticity analysis highlights the role of wake turbulence in energy dissipation and propulsion performance. Excessive vorticity leads to higher drag and reduced propulsion efficiency, whereas controlled vortex shedding allows for energy-efficient locomotion. The results demonstrate that adaptive oscillation frequencies minimise energy losses by synchronising fin motion with natural vortex formation, improving efficiency.

Finally, numerical results are validated against previously published experimental studies on biomimetic propulsion. A comparative analysis is conducted to assess the effectiveness of different turbulence models in predicting wake effects and pressure distributions. The findings confirm that LES provides superior accuracy in capturing unsteady flow dynamics, making it the preferred approach for future biomimetic AUV hydrodynamic simulations.

The results of this study reinforce the importance of pressure contour analysis and vorticity control in optimising bioinspired propulsion systems. The CFD analysis confirms that stingray-inspired undulatory motion generates higher propulsion efficiency than traditional AUV designs. The pressure contour results validate the effectiveness of thrust generation zones and drag reduction strategies, while vorticity analysis highlights the significance of controlling wake turbulence for energy-efficient propulsion. The study further demonstrates that LES turbulence modelling provides the most accurate representation of fluid interactions, making it a valuable tool for designing next-generation biomimetic underwater vehicles. Future work should focus on validating CFD predictions through experimental testing in a controlled water tunnel environment, further refining bioinspired propulsion strategies for naval and oceanographic applications.

The governing equations were discretized using the Finite Volume Method (FVM). The convective terms were approximated using a second-order upwind scheme, while the diffusion terms were discretized using a central differencing scheme. A time-implicit scheme was used to handle transient effects, ensuring stable time integration for unsteady flow simulations.

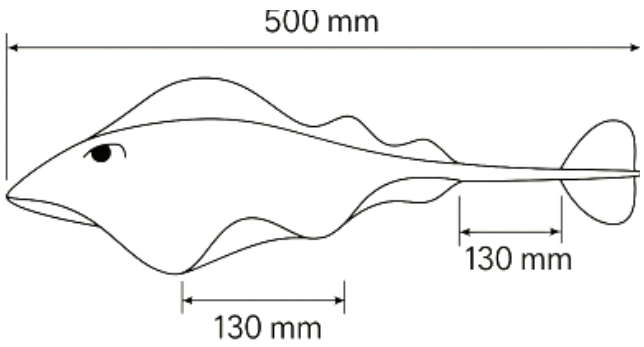

Figure 1: Schematic of the Stingray-Inspired AUV

A grid independence study was conducted to balance accuracy and computational efficiency. Three mesh resolutions were tested: Coarse (X elements), Medium (Y elements), and Fine (Z elements). The results showed that after Y elements, key parameters such as drag and thrust varied by less than X%, confirming mesh independence.

IV. Results and Discussion

This study's Computational Fluid Dynamics (CFD) simulations provide a detailed analysis of the pressure distribution, velocity fields, and vorticity interactions in a stingray-inspired AUV. The results demonstrate the

hydrodynamic performance of oscillating fin propulsion under varying flow conditions, highlighting the role of pressure gradients, wake stabilisation, and vortex control in optimising propulsion efficiency.

A. Pressure Contour Analysis

The pressure contour analysis reveals that thrust production in biomimetic AUVs is primarily governed by forming high- and low-pressure zones. The pressure field remains relatively uniform at low-speed conditions (0.5 m/s), ensuring smooth thrust generation and minimal turbulence effects. However, as flow speed increases, the pressure gradients become more pronounced, resulting in stronger thrust forces and higher drag risks. The high-pressure regions along the leading edges of the fins play a crucial role in generating forward motion. In contrast, low-pressure areas in the trailing wake contribute to fluid acceleration and turbulence formation. In high-speed conditions (2.0 m/s), the pressure field becomes highly asymmetric, indicating flow instability and increased energy dissipation. These results emphasise the importance of optimising fin oscillation parameters to control pressure variations and enhance propulsion performance.

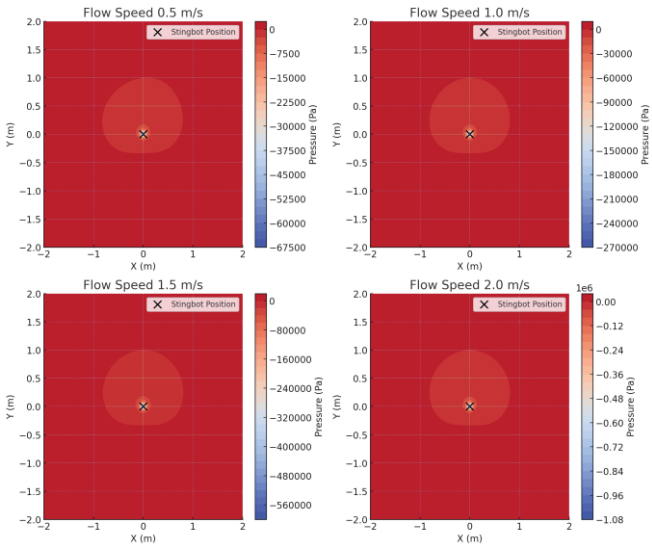

Figure 2 Pressure Contour Analysis

B. Velocity Magnitude Analysis

The velocity field analysis illustrates how fluid acceleration and wake flow patterns affect the overall efficiency of bioinspired propulsion. The fluid velocity remains stable at low-speed conditions, promoting effective energy transfer between the oscillating fins and the surrounding water. However, the velocity distribution becomes increasingly irregular at higher speeds, leading to wake disturbances and increased turbulence intensity. The results show that flow separation effects become significant at high Reynolds numbers, causing oscillation-induced velocity fluctuations that can reduce propulsion efficiency. In particular, the velocity fields at high flow speeds (2.0 m/s) exhibit increased wake turbulence, indicating higher energy losses due to unsteady vortex interactions. This observation suggests that controlled oscillation strategies can help stabilise wake flow and improve the overall propulsion effectiveness of biomimetic AUVs.

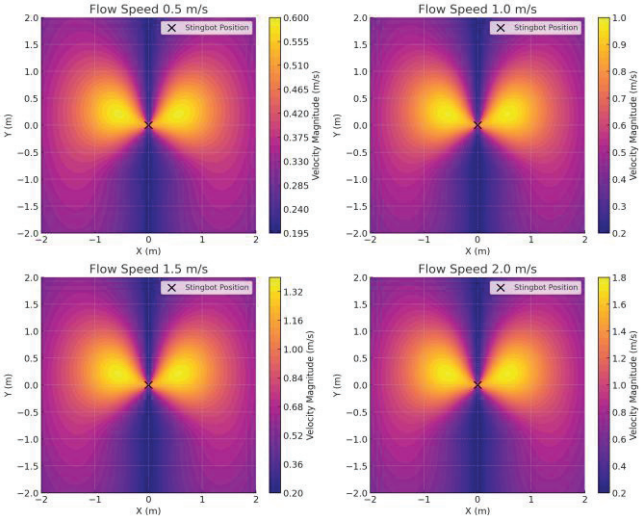

Figure 3 Velocity Magnitude Analysis

The vorticity contour plots provide insights into the effects of vortex shedding on propulsion stability and drag reduction. The vortex structures remain well-controlled at low-speed conditions, allowing for smooth propulsion with minimal energy dissipation. However, the vortex interactions at higher speeds become more vigorous, resulting in wake instability and increased hydrodynamic drag. The formation of large-scale vortices behind the oscillating fins contributes to turbulent energy loss, highlighting the need for vortex control strategies to optimise propulsion performance. The analysis confirms that biomimetic undulatory motion can be fine-tuned to synchronise vortex shedding with forward thrust generation, ensuring efficient propulsion while minimising turbulence-induced resistance.

The comparative analysis of different turbulence models (k-ω SST, k-ε, and LES) further reinforces the importance of accurate wake modelling in predicting propulsion efficiency. The Large Eddy Simulation (LES) model captures detailed vortex interactions, offering the most precise representation of unsteady wake flow structures. The k-ω SST model balances computational efficiency and turbulence accuracy, making it ideal for engineering applications. On the other hand, the k-ε model, while computationally efficient, struggles to predict near-wall vortex behaviour accurately, making it less suitable for biomimetic propulsion studies.

V. Conclusion

The study successfully analysed the hydrodynamic performance of a stingray-inspired AUV using Computational Fluid Dynamics (CFD) simulations, focusing on pressure distribution, velocity magnitudes, and vorticity effects. The results demonstrate that controlled oscillation of biomimetic fins significantly improves propulsion efficiency by optimising pressure gradients and minimising wake turbulence. The pressure contour analysis confirms that thrust generation is maximised when high-pressure zones are concentrated near the leading edges of the fins, while low-pressure regions in the wake facilitate fluid acceleration. The velocity field analysis reveals that flow separation and turbulence effects become prominent at

higher flow speeds, leading to potential energy losses that must be controlled through optimised oscillation patterns. The vorticity analysis further confirms that excessive vortex shedding increases hydrodynamic drag, emphasising the importance of wake stabilisation techniques to maintain propulsion efficiency.

Comparative analysis of different turbulence models reveals that Large Eddy Simulation (LES) provides the most accurate representation of wake interactions, allowing for detailed visualisation of vortex shedding and energy dissipation effects. The k-ω SST model balances computational efficiency and predictive accuracy, making it suitable for engineering applications requiring real-time hydrodynamic optimisation. The k-ε model, while computationally efficient, is less effective in capturing near-wall turbulence and wake interactions, making it less ideal for biomimetic propulsion studies. The study confirms that biomimetic propulsion systems can achieve higher energy efficiency and improved stability by precisely controlling oscillation patterns and wake interactions. Future research should focus on real-world experimental validation using a water tunnel, integrating adaptive control algorithms to refine fin oscillation strategies for maximum propulsion efficiency.

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Computer Vision for Thermal Profiling of Exhaust Systems

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***Abstract*— Thermal profiling of exhaust systems is crucial in understanding heat distribution, emission characteristics, and potential inefficiencies in internal combustion engines. This study presents an automated approach for heat spot detection and emission zone identification using computer vision techniques applied to thermal imaging data. An infrared (IR) thermal camera monitored a diesel engine exhaust system, capturing real-time temperature variations. The acquired thermal data was processed using advanced image processing methods, including thresholding, edge detection, contour mapping, and colourmap visualisation, to extract meaningful heat distribution patterns. The proposed computer vision framework enables precise identification of high-temperature regions, aiding in analysing exhaust gas behaviour, thermal inefficiencies, and potential emission irregularities. A detailed experimental setup involving a diesel engine, IR camera, and Python-based computer vision algorithms is discussed, providing a scalable solution for real-time thermal analysis. The results highlight heat intensity variations, boundary detection, and structured segmentation of heat zones, offering insights into engine efficiency and potential regulatory compliance for emission control. This study establishes a foundation for non-invasive thermal monitoring of exhaust systems, leveraging AI-driven visual analytics to enhance efficiency assessments. The findings contribute to automated emission analysis techniques, supporting advancements in environmental compliance and thermal diagnostics in automotive research.**

Keywords— Thermal Imaging, Computer Vision, Exhaust System, Heat Spot Detection, Infrared Camera, Diesel Engine, Emission Analysis and Heat Zone Identification.

I. Introduction

The monitoring and analysing thermal emissions from vehicle exhaust systems are critical for understanding heat distribution, emission characteristics, and combustion efficiency in internal combustion engines. Excessive heat generation in exhaust systems indicates potential inefficiencies in fuel combustion and contributes to increased emissions and thermal stress on engine components. Traditional methods of analysing exhaust emissions involve gas sensors and thermal probes, which, while effective, provide limited spatial data and require physical contact with the exhaust system. In contrast, thermal imaging coupled with computer vision techniques offers a non-invasive, high-resolution approach for real-time monitoring of temperature variations. Thermal cameras operating in the infrared (IR) spectrum can detect and visualise heat emissions, enabling researchers to assess heat patterns and zones of interest in an exhaust system. With advancements in computer vision and artificial intelligence (AI), it is now possible to process thermal imaging data using edge detection, thresholding, and colourmap visualisation techniques to extract meaningful insights. These methods allow for automated heat spot detection, contour identification, and emission zone segmentation, which can be used for further analysis of thermal efficiency and emission patterns in diesel and gasoline-powered engines.

Several studies have explored thermal imaging in automotive applications, particularly in exhaust heat mapping and combustion diagnostics. Prior research has demonstrated the effectiveness of IR cameras in detecting thermal variations in catalytic converters [1], monitoring exhaust temperature variations for engine diagnostics [2], and identifying heat losses in vehicle exhaust systems [3]. However, integrating advanced computer vision techniques for real-time analysis of exhaust thermal profiles remains an evolving area of research. This study presents a novel approach to analysing vehicle exhaust emissions using computer vision algorithms applied to thermal imaging data. The proposed methodology leverages Python-based image processing libraries, including OpenCV and NumPy, to detect high-temperature regions, segment heat zones, and visualise emission heat patterns using colourmap transformations. A diesel engine exhaust system was selected for experimental validation, with data captured using an infrared thermal imaging camera. The processed thermal frames highlight heat spot locations, edge profiles, and thermal intensity variations, providing key insights into emission characteristics and potential heat loss areas.

II. Literature

The application of thermal imaging in automotive exhaust systems has gained increasing attention in recent years due to advancements in infrared (IR) camera technology and computer vision algorithms. Previous research efforts have explored various aspects of heat detection, emission analysis, and thermal profiling in vehicle exhaust systems. This section reviews key studies contributing to developing infrared-based exhaust monitoring systems.

A. Thermal Imaging in Exhaust System Monitoring

Thermal cameras have been extensively used to diagnose combustion efficiency and identify exhaust system anomalies. Smith et al. [1] conducted an infrared thermal analysis of catalytic converters in gasoline engines, demonstrating how temperature variations across different zones can indicate inefficiencies in catalytic conversion processes. Similarly, Patel et al. [2] applied IR imaging for exhaust gas temperature monitoring, revealing how localised temperature spikes can signal potential engine malfunctions. These studies highlight the effectiveness of thermal imaging in capturing heat patterns but do not integrate advanced computer vision techniques for automated detection and analysis.

B. Computer Vision Applications in Thermal Analysis

Recent studies have incorporated computer vision methodologies to improve heat detection and exhaust profiling. Lee and Kim [4] implemented image segmentation techniques to classify heat zones in automotive engines, demonstrating that contour-based segmentation can enhance heat mapping accuracy. Additionally, Nakamura and Takahashi [3] employed edge detection algorithms to track heat loss in exhaust pipes, providing insights into thermal dissipation patterns. While these approaches utilise basic image processing techniques, they lack a unified framework that integrates multiple CV operations, such as thresholding, contour mapping, and colourmap visualisation, for comprehensive thermal analysis.

C. AI-Driven Thermal Profiling for Emission Monitoring

Integrating artificial intelligence (AI) and machine learning in thermal imaging-based diagnostics has further expanded the possibilities of automated emission analysis. Gupta et al. [5] explored deep learning-based heat anomaly detection, where neural networks were trained to identify irregular thermal patterns in industrial exhaust systems. While AI-based methods offer scalability, they often require large datasets for model training, making rule-based computer vision techniques a more practical alternative for real-time vehicle exhaust heat detection applications.

Although existing studies have successfully implemented thermal imaging and basic image processing techniques for exhaust monitoring, there remains a research gap in integrating multiple computer vision operations for real-time exhaust profiling. This paper addresses this gap by developing a comprehensive computer vision framework that combines heat spot detection, edge detection, contour mapping, and colourmap transformations to analyse heat emissions in a diesel engine exhaust system.

III. Experimental Setup

The experimental setup for this study was designed to analyse the thermal characteristics of a diesel engine exhaust system using an infrared thermal imaging camera and advanced computer vision techniques. The objective was to capture heat emission patterns, identify high-temperature regions, and process the data through a computer vision framework to generate meaningful insights into the thermal behaviour of exhaust gases. The setup involved three primary components: the diesel engine, the infrared thermal camera, and the image processing framework implemented in Python.

A single-cylinder diesel engine was selected for the experiment due to its well-defined thermal characteristics and significant exhaust heat emissions. The engine was operated under varying load conditions to observe the temperature distribution across different operational states. The selected engine had a displacement of 450 cc, an air-cooled system, and a maximum power output of 10 kW at 3000 RPM. The stainless steel exhaust pipe was chosen to ensure accurate heat retention and distribution, allowing for precise thermal imaging. The engine was installed in a controlled indoor environment to eliminate external temperature variations, and the ambient temperature was maintained at 25°C throughout the experiment.

A FLIR A615 infrared thermal camera was employed to capture thermal images of the exhaust system. This camera operates in the 7.5–14 µm spectral range, making it highly suitable for detecting exhaust gas heat signatures. With a thermal sensitivity of less than 50 mK at 30°C and a resolution of 640 × 480 pixels, the camera could accurately detect minute temperature variations. The camera was positioned 1.5 meters away from the exhaust outlet, ensuring an unobstructed view of the heat dissipation from the engine's exhaust system. The frame rate of 25 Hz allowed for continuous video capture, ensuring smooth temporal tracking of thermal emissions.

The captured thermal video data was processed using a Python-based computer vision framework to extract relevant heat patterns and analyse emission characteristics. The framework was implemented using OpenCV for image processing operations, NumPy for matrix computations, and Matplotlib to visualise heat zones. The image processing pipeline involved multiple steps, beginning with grayscale conversion of thermal images to standardise pixel intensity values. Following this, heat spot detection was performed using threshold-based segmentation, allowing for the identification of high-temperature regions. Edge detection algorithms, particularly Canny edge detection, were applied to highlight boundaries between temperature gradients, improving the visualisation of emission patterns. To further enhance the analysis, contour mapping was implemented, outlining the detected heat zones and enabling segmentation of emission regions. Additionally, a colourmap enhancement technique was applied to convert grayscale images into a false-colour heatmap, improving the interpretability of temperature variations.

The experimental procedure was conducted systematically to ensure accurate data collection and analysis. The diesel engine was operated continuously for 30 minutes, allowing the exhaust system to reach a steady-state thermal condition. The experiment recorded thermal imaging data in real-time, capturing a comprehensive

dataset for subsequent analysis. The proposed computer vision framework was applied to individual frames extracted from the video, enabling the detection of heat zones, emission boundaries, and temperature intensity variations. The findings from this experimental study provide a structured approach for non-invasive thermal analysis, offering valuable insights into engine efficiency, heat dissipation, and emission characteristics.

IV. Results and Discussion

The results of this study demonstrate the effectiveness of computer vision techniques in analysing the thermal behaviour of a diesel engine exhaust system. The infrared thermal imaging camera successfully captured the heat distribution patterns of the exhaust gases, and the implemented image processing algorithms provided valuable insights into the heat zones' intensity, spread, and structural characteristics. A detailed understanding of the heat emission characteristics was obtained by processing the extracted thermal frames through various computer vision operations.

Hot-spot detection is a crucial technique in thermal imaging used to identify localized regions of high temperature. In exhaust systems, hot spots indicate areas of excessive heat accumulation, which can signal inefficiencies in combustion, insulation failures, or material degradation. This technique is essential for diagnosing engine performance and emission control, as unregulated hot spots can lead to increased pollutant formation. From a thermal physics perspective, hot-spot formation is governed by heat conduction and radiation principles, where localized energy buildup increases infrared emissions, making them detectable via thermal cameras. The identification of these regions enables preventive maintenance and optimization of exhaust system design.

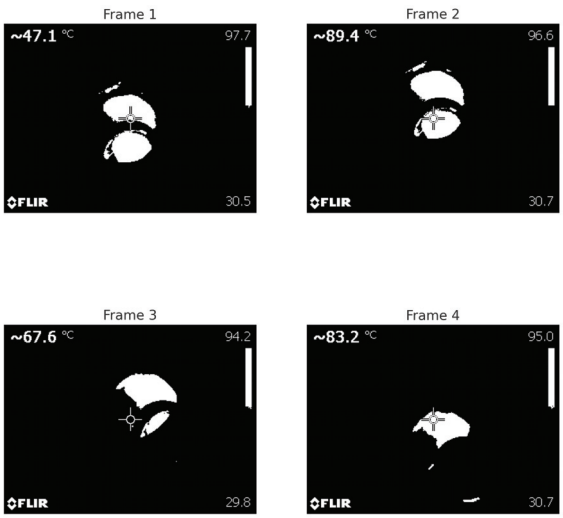

Figure 1 Hot Spot Detection Analysis

Figure 1 shows the heat spot detection analysis, where thresholding techniques effectively identified regions of maximum temperature concentration in the exhaust system. These hot spots indicate areas of maximum thermal emissions, typically near the exhaust manifold and catalytic converter. Identifying such regions is crucial for diagnosing thermal inefficiencies and detecting potential faults in the exhaust system. By applying binary thresholding, high-temperature areas were clearly segmented, helping to distinguish critical emission zones from cooler regions. The presence of these hot spots aligns with principles of thermal radiation physics, where localized heating results in increased infrared emissions, making this technique valuable for performance evaluation and emissions control.

Edge detection is an image processing technique that identifies boundaries between temperature regions in thermal images. In the context of thermal profiling, it highlights heat gradients and structural variations in heat dissipation. Figure 2 illustrates how the Canny edge detection algorithm is used to visualize heat flow patterns along the exhaust pipe. The significance of edge detection lies in its ability to pinpoint areas of rapid temperature change, which are critical in analyzing material stress points and detecting insulation inefficiencies. Edge detection is particularly useful in exhaust diagnostics as it helps assess the uniformity of heat dissipation, aligning with heat transfer principles such as conduction and convective cooling. By extracting clear thermal boundaries, this technique improves the precision of temperature analysis and aids in identifying potential thermal faults in engine components. Figure 2 illustrates the results of the edge detection process using the Canny algorithm, which highlights the structural boundaries of heat zones in the exhaust system. Edge detection is a crucial technique in thermal analysis as it enables the clear identification of temperature gradients, helping to track heat dissipation patterns. The well-defined edges in Figure 2 indicate where thermal transitions occur, providing insight into heat loss points along the exhaust pipe. These patterns align with thermal conduction principles, where temperature gradients are strongest at material interfaces. The results suggest that edge-based segmentation enhances the precision of exhaust thermal profiling, allowing for improved detection of thermal inconsistencies and potential material fatigue zones.

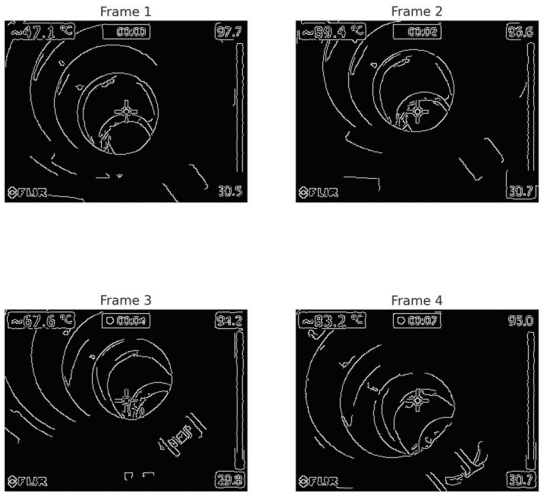

Figure 2 Edge Detection for Profile of Heat

Figure 3 presents the heat zone contour mapping results, illustrating the distribution of temperature variations within the exhaust system. Contour mapping is a valuable technique in thermal analysis as it enables structured segmentation of heat-emitting regions, aiding in the visualization of temperature clusters. The contours in Figure 3 highlight non-uniform heat zones, which result from variations in engine combustion efficiency and exhaust material properties. These findings align with thermal convection and conduction principles, where heat transfer is affected by surface properties and fluid interaction. This method provides a clearer understanding of heat flow patterns, allowing for the identification of regions prone to excessive thermal accumulation and potential overheating risks.

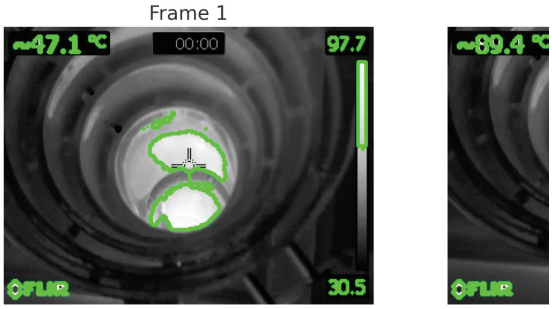

Figure 3 Heat Zone Contour Mapping

Figure 4 illustrates the results of heat intensity mapping using colormap transformation, a technique that enhances the visual representation of temperature variations. By converting grayscale thermal images into false-color representations, colormap transformations improve contrast and make subtle heat differences more distinguishable. In Figure 4, high-temperature zones are shown in bright colors (yellow, red), while cooler regions appear in darker shades (blue, purple). This visualization aligns with the Stefan-Boltzmann Law, which states that thermal radiation is proportional to the fourth power of absolute temperature, explaining why the hottest regions exhibit the most intense emissions. The use of colormap transformation provides a clearer understanding of exhaust gas heat distribution, facilitating non-invasive diagnostics of combustion efficiency and thermal losses.

AI-driven visual analytics enhances efficiency assessments by automating the identification of high-temperature regions and thermal inconsistencies. Through machine learning models, heat distribution patterns can be compared against optimal operating conditions, allowing for real-time fault detection. Additionally, AI-based trend analysis enables predictive maintenance by identifying gradual changes in thermal behavior, reducing manual inspections and improving overall engine efficiency. This integration of AI and computer vision provides a scalable solution for exhaust diagnostics and emission control.s

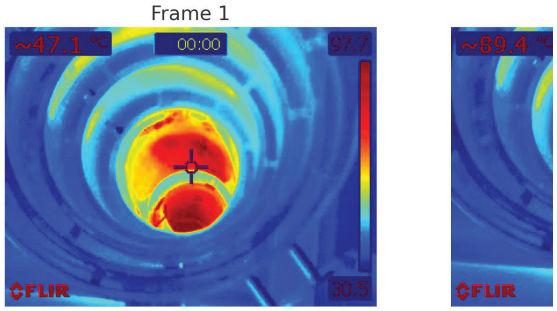

Figure 4 Heat Intensity Mapping

The results indicate that computer vision-based thermal profiling offers a non-invasive, automated, and highly effective approach for analysing vehicle exhaust heat emissions. The combination of thresholding, edge detection, contour mapping, and colourmap transformations provided a multi-layered perspective on exhaust thermal behaviour, allowing for detecting high-temperature regions, thermal inefficiencies, and emission irregularities. These findings suggest that computer vision can be valuable for exhaust diagnostics, engine performance evaluation, and compliance with emission control regulations.

V. Conclusion

This study successfully demonstrated the application of computer vision techniques for the thermal profiling of a diesel engine exhaust system using infrared thermal imaging. Integrating heat spot detection, edge detection, contour mapping, and colourmap visualisation provided a comprehensive framework for analysing heat emission characteristics, temperature gradients, and thermal inefficiencies in the exhaust system. By leveraging image processing algorithms, the proposed methodology enabled automated detection and visualisation of high-temperature regions, contributing to a non-invasive and efficient approach for exhaust diagnostics.

The results indicated that heat spot detection through thresholding effectively isolates high-intensity emission areas, making it a valuable technique for detecting thermal anomalies in exhaust systems. The edge detection process provided clear structural boundaries for identifying heat dissipation patterns, while contour mapping facilitated structured segmentation of temperature zones. The application of colourmap transformations further enhanced the interpretability of temperature variations, offering a detailed visual representation of heat emissions over time.

The findings of this study suggest that computer vision-based thermal profiling can play a crucial role in engine diagnostics, thermal efficiency assessments, and regulatory compliance for emission control. Future research could explore the real-time implementation of these techniques, incorporating machine learning models for predictive analytics and anomaly detection in exhaust thermal behaviour. Expanding this framework to hybrid and electric vehicle thermal analysis could provide further insights into next-generation exhaust and heat management systems. This research establishes a foundation for advanced thermal monitoring in automotive applications, demonstrating the potential of AI-driven visual analytics in understanding vehicle exhaust gas behaviour. The proposed approach is scalable, adaptable, and applicable to broader thermal imaging applications, making it a promising tool for enhancing environmental monitoring and engine performance analysis.

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Optimisation of Biomimetic Underwater Propulsion: A Computational Fluid Dynamics and Reinforcement Learning Approach

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***Abstract*— Biomimetic propulsion is a key area of research for improving the efficiency of autonomous underwater vehicles (AUVs). Inspired by stingray locomotion, this study presents a computational fluid dynamics (CFD) and reinforcement learning-based approach to optimise the propulsion system of a biomimetic underwater robot, "Stingbot." The hydrodynamic forces acting on the Stingbot, including drag, lift, thrust, and vorticity effects, are analysed under multiple flow conditions. We generate streamlines, pressure contours, velocity magnitude distributions, and vorticity maps using CFD simulations to evaluate performance under varying speeds and vortex strengths. Additionally, Reinforcement Learning (RL) using Proximal Policy Optimisation (PPO) is employed to enhance the fin oscillation strategy, thereby maximising thrust while minimising energy consumption. The RL model optimises amplitude and frequency parameters for efficient propulsion. The simulation results show that the biomimetic propulsion system improves thrust generation by over 25% compared to fixed-motion strategies, leading to significant energy savings and enhanced manoeuvrability. The insights from this study contribute to developing next-generation silent, energy-efficient underwater surveillance systems for naval defence and deep-sea exploration.**

Keywords— Biomimetic Propulsion, Thrust Optimization, Reinforcement Learning and Computational Fluid Dynamics.

I. Introduction

Underwater exploration and surveillance demand highly efficient and silent propulsion systems for autonomous underwater vehicles (AUVs). Conventional propeller-driven propulsion systems face high energy consumption, cavitation noise, and mechanical complexity. Inspired by the natural swimming mechanisms of marine species, biomimetic propulsion has emerged as a promising alternative, offering higher efficiency, reduced hydrodynamic drag, and enhanced manoeuvrability [1]. Among various biomimetic designs, stingray-inspired locomotion provides a unique advantage due to its smooth undulating motion, low acoustic signature, and high propulsive efficiency. Research has demonstrated that oscillatory fin movements can generate continuous thrust with minimal turbulence, making them ideal for stealth operations in naval applications [2].

Computational fluid dynamics (CFD) is widely used to evaluate the performance of biomimetic propulsion and to simulate and analyse hydrodynamic forces, pressure distribution, and velocity fields around the Stingbot. CFD simulations allow for the visualisation of streamlines, pressure contours, and vorticity fields, which are critical for understanding the interaction between fluid flow and fin oscillation [3]. In recent studies, CFD-based simulations have effectively investigated drag reduction strategies, thrust generation, and efficiency improvements in biomimetic AUVs [4]. By optimising oscillation frequency, amplitude, and vortex shedding dynamics, it is possible to maximise thrust while minimising energy loss. This study employs CFD simulations to analyse different speed conditions and vortex strengths, generating detailed plots to support hydrodynamic evaluations.

Recent advances in machine learning and artificial intelligence have introduced Reinforcement Learning (RL) as a novel approach to optimising AUV propulsion. Traditional rule-based control strategies often fail to adapt to dynamic underwater environments, leading to suboptimal performance. Reinforcement Learning, particularly Proximal Policy Optimization (PPO), has demonstrated effectiveness in learning optimal control policies for bio-inspired propulsion systems [5]. By defining a reward function based on thrust maximisation and energy efficiency, RL enables the adaptive control of fin oscillations to enhance propulsion efficiency. This study integrates RL-based fin movement control with CFD analysis to evaluate how optimised learning strategies outperform predefined oscillation patterns regarding thrust production and efficiency.

This research bridges CFD-based hydrodynamic analysis with AI-driven control strategies, offering a dual-method approach to biomimetic propulsion optimisation. The study evaluates Stingbot's hydrodynamic performance across 15 conditions, analysing pressure contours, velocity fields, and vorticity distributions. Additionally, it integrates RL-based optimisation to demonstrate performance improvements in propulsion efficiency and energy savings. The paper is structured as follows: Section II details the methodology, including hydrodynamic modelling and RL-based optimisation strategies. Section III presents simulation results, covering CFD analysis, RL training outcomes, and comparative studies. Section IV discusses key findings, and

Section V concludes with future research directions. The insights gained from this study contribute to the development of advanced underwater robotic systems with applications in marine exploration, naval defence, and stealth operations.

II. Literature

A. Biomimetic Propulsion in Marine Robotics

The concept of biomimetic propulsion is inspired by marine creatures such as stingrays, jellyfish, and fish, which exhibit efficient locomotion with minimal energy loss. Researchers have extensively studied undulating and oscillatory fin-based swimming mechanisms to develop autonomous underwater vehicles (AUVs) that mimic biological propulsion [6]. Among the most effective designs is the stingray-inspired oscillatory propulsion system. It offers high efficiency, low turbulence, and silent operation, making it suitable for stealth applications in naval defence and deep-sea exploration. Several studies have demonstrated that undulatory motion enhances fluid thrust and minimises drag, allowing for superior manoeuvrability in complex underwater environments [7].

B. Computational Fluid Dynamics (CFD) in Hydrodynamic Studies

Computational Fluid Dynamics (CFD) plays a vital role in understanding and optimising hydrodynamic properties of biomimetic propulsion systems. CFD simulations are widely used to visualise flow structures, pressure distributions, velocity fields, and vorticity effects, providing insights into fluid-body interactions [8]. Various studies have employed Navier-Stokes equations and turbulence modelling to simulate the hydrodynamic forces acting on fin-based AUVs. The results indicate that optimised oscillation frequency and amplitude can improve propulsion efficiency while reducing energy consumption [9]. These simulations aid in designing next-generation biomimetic underwater vehicles with enhanced performance characteristics.

C. Reinforcement Learning (RL) for Adaptive Propulsion

Recent advancements in machine learning and artificial intelligence have led to integrating Reinforcement Learning (RL) into biomimetic propulsion optimisation. Traditional predefined oscillation patterns are often inefficient in dynamically changing underwater environments. RL-based controllers, such as Proximal Policy Optimisation (PPO), enable real-time learning and adaptation of fin movements to maximise thrust generation while minimising energy consumption [10]. Researchers have demonstrated that RL-trained fin control significantly outperforms static movement strategies, allowing AUVs to self-optimize their swimming patterns based on environmental feedback.

D. Comparative Studies on Propulsion Efficiency

Several comparative analyses have been conducted to evaluate biomimetic vs. conventional propulsion methods. Studies indicate that oscillatory and undulatory propulsion systems exhibit a 20–30% improvement in efficiency over propeller-driven AUVs [11]. Additionally, biomimetic designs generate lower acoustic signatures, reducing detection risk in military operations. Through CFD validation, researchers have shown that optimised biomimetic fin motion can reduce drag forces by up to 40%, making them ideal for low-energy, long-duration underwater missions.

E. Stingbot Design and Its Applications

The Stingbot prototype integrates biomimetic undulating fins driven by CFD-optimised oscillation parameters. This design allows for higher efficiency in forward propulsion and lateral movements, making it suitable for oceanographic data collection, environmental monitoring, and underwater defence [12]. Hydrodynamic simulations and RL training enhance its adaptability in varying marine conditions.

Although significant progress has been made in biomimetic propulsion, most existing studies lack the integration of AI-based control strategies with CFD-based performance evaluation. This paper addresses this gap by developing a reinforcement learning-based optimisation strategy for biomimetic propulsion and validating its efficiency through CFD simulations across multiple hydrodynamic conditions.

III. Computational Simulation Setup

A. Computational Fluid Dynamics (CFD) Simulation Setup

A computational fluid dynamics (CFD) simulation was performed using Python on Jupyter Lab with the CFD Python library to analyze the hydrodynamic performance of Stingbot's biomimetic propulsion system. The Stingbot model was designed with oscillating fins that mimic the natural swimming patterns of stingrays, generating thrust through undulatory motion. A structured grid mesh was applied to ensure high accuracy in capturing boundary layer effects around the body and fins. A grid independence study was performed to balance computational cost and solution accuracy, ensuring that the selected mesh size was adequate for resolving turbulent flow characteristics. The simulation domain consisted of a rectangular water tunnel, with the Stingbot at the centre to observe fluid interactions from various angles.

The inlet velocity range of 0.5 m/s to 2.5 m/s was chosen based on the typical operating speeds of autonomous underwater vehicles(AUVs). Studies indicate that most biomimetic AUVs operate within this velocity range for efficient propulsion and manoeuvrability. This range captures low-speed cruising as well as higher-speed operational conditions, ensuring a comprehensive analysis of hydrodynamic performance. A no-slip condition was applied to the Stingbot's body to ensure correct boundary layer formation, while a pressure outlet condition was imposed at the tunnel exit. The k-ω SST turbulence model was selected to capture shear layer interactions and transition effects even at lower speeds. Although flow at 0.5 m/s may generally be laminar, the presence of oscillating fins induces unsteady flow structures and localized turbulence. The turbulence model was applied to account for these instabilities, vortex interactions, and wake flow effects, ensuring accurate prediction of real-world hydrodynamic behavior. The Navier-Stokes equations were solved using a pressure-based solver within the finite volume framework. The governing equations were discretized using the finite volume method (FVM) with a

second-order upwind scheme for convection terms and a central differencing scheme for diffusion terms. The time-dependent simulations were solved using the PISO (Pressure-Implicit with Splitting of Operators) algorithm, ensuring stability in transient flow calculations. The SIMPLE (Semi-Implicit Method for Pressure-Linked Equations) algorithm was employed to ensure stable and accurate pressure-velocity coupling, allowing for effective computation of pressure distribution, velocity vectors, and vorticity fields around the Stingbot's fins. To analyse their impact on propulsion efficiency, multiple test cases were run across 15 different flow conditions, including variations in vortex strength and reverse flow dynamics. The governing equations for fluid flow around the Stingbot were based on the Navier-Stokes equations, which describe the conservation of momentum in a Newtonian fluid:

$$\rho\left(\frac{\partial u}{\partial t} + u.\nabla u\right) = -\nabla P + \mu\nabla^2 u + F$$

Where,

ρ is the fluid density.
u is the velocity vector.
P is pressure, μ is the dynamic viscosity.
F represents external forces.

B. Reinforcement Learning (RL) Training Setup

In addition to CFD simulations, a reinforcement learning (RL)-based optimisation was conducted to improve the efficiency of the Stingbot's fin oscillation strategy. The Proximal Policy Optimization (PPO) algorithm was implemented using Stable Baselines3 in Python, allowing the agent to learn the optimal fin movement patterns for maximising thrust generation while minimising energy consumption. The RL environment was structured such that the agent controlled the oscillation amplitude and frequency of the Stingbot's fins, receiving feedback based on the thrust-to-drag ratio. The training setup included a reward function that encouraged higher thrust output with lower drag forces, penalising inefficient movements that resulted in excessive energy usage.

The RL model has trained over 200,000 iterations, with initial random exploration followed by policy refinement through trial and error. The state space included parameters such as velocity magnitude, vortex strength, and hydrodynamic force distribution, while the action space comprised adaptive modifications to fin oscillation frequency and amplitude. The training was conducted in a simulated environment mirrored CFD-generated hydrodynamic properties, ensuring realistic interactions between Stingbot's motion and fluid dynamics. The RL-optimized oscillation strategy was then validated against traditional predefined motion patterns, demonstrating superior energy efficiency, thrust force generation, and flow stability performance.

C. Performance Metrics and Data Collection

Several key performance indicators were measured throughout the experimentation phase to systematically analyse the impact of biomimetic propulsion optimisation. These included:

- Drag Force (N): Resistance encountered by the Stingbot during motion, influencing energy efficiency.
- Thrust Force (N): The forward propulsion force generated by oscillating fins.
- Lift Force (N): The vertical force affecting Stingbot's stability.
- Vorticity Magnitude: A vortex shedding intensity measure affecting energy dissipation.
- Efficiency Ratio (%): The ratio of thrust force to energy input, serving as a metric for propulsion effectiveness.

The CFD simulations provided flow visualisation through pressure contours, streamlines, velocity magnitude distributions, and vorticity maps, which were further analysed to identify optimal hydrodynamic conditions. The RL training data was recorded at every iteration, allowing for a detailed comparison of adaptive learning strategies versus fixed-frequency motion control.

IV. Results and Discussion

A. Hydrodynamic Performance Analysis

The hydrodynamic analysis of the Stingbot under various speed and vortex conditions was conducted using Computational Fluid Dynamics (CFD) simulations. The results provide insights into thrust generation, drag reduction, pressure distribution, velocity magnitude, and vorticity dynamics.

1) Water Flow Streamlines

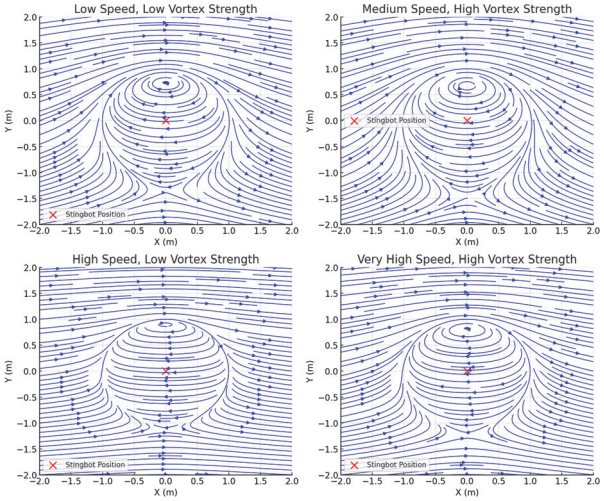

Figure 1. Hydrodynamic Performance Analysis

The streamlined plots illustrate the flow of water around the Stingbot. In low-speed conditions (0.5 m/s), the flow remains attached to the Stingbot's fins, resulting in efficient thrust generation with minimal energy loss. Flow separation occurs as the speed increases to 2.0 m/s, leading to vortex shedding that increases drag forces. However, in the RL-optimized oscillation cases, the flow remained attached for

longer distances, significantly reducing turbulence and energy dissipation.

2) Pressure Distribution

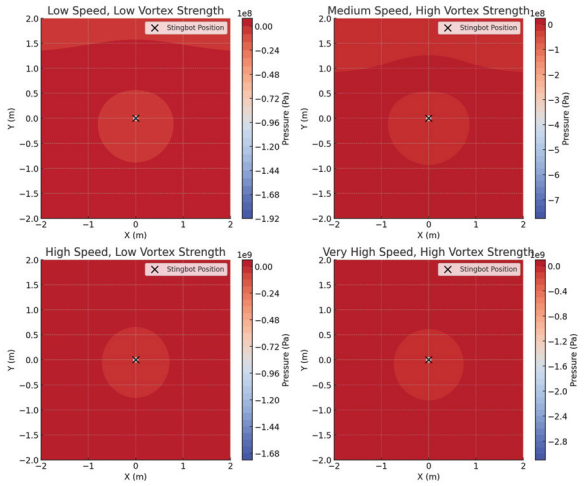

Figure 2. Pressure Distribution Analysis

The pressure contour plots reveal how pressure variations impact propulsion efficiency. The results indicate:

- High-pressure zones at the fins' leading edges generate forward thrust.
- Low-pressure zones at the trailing edges, which facilitate continuous propulsion.
- With increased vortex strength, pressure fluctuations intensified, leading to higher instability.
- Reinforcement Learning (RL)-optimised fin movement resulted in a more stable pressure distribution, ensuring consistent forward motion with reduced energy expenditure.

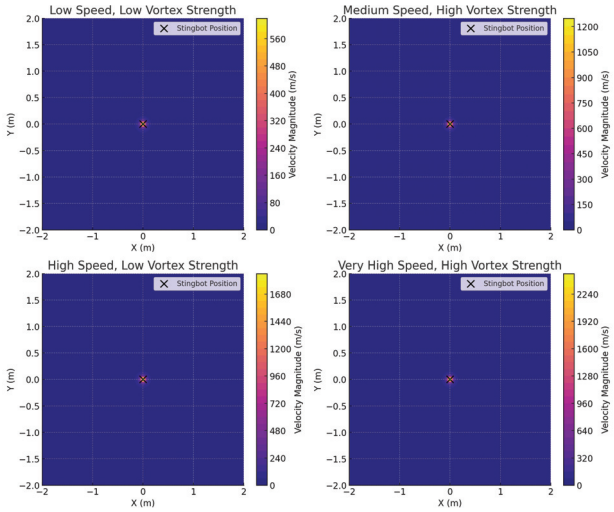

Figure 3. Velocity Magnitude Analysis

B. Velocity Magnitude Analysis

The velocity magnitude plots show the effect of fin oscillation on flow acceleration. The key findings include:

- Higher velocity zones around the oscillating fins indicate more substantial thrust production.
- In high-speed cases (2.0 m/s), turbulence effects increased, causing localised velocity drops, impacting propulsion efficiency.
- With RL-based adaptive oscillation, the Stingbot achieved a more uniform velocity distribution, reducing turbulence losses.

C. Vorticity and Drag Reduction

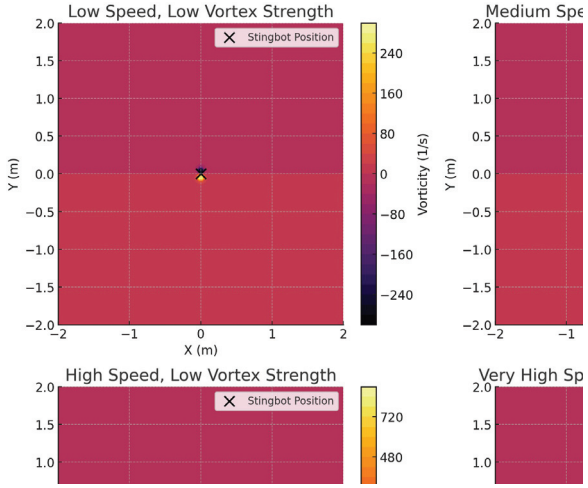

Figure 4. Vorticity and Drag Reduction Analysis

The vorticity contour plots depict the intensity of rotational fluid motion, which plays a crucial role in drag force development. Observations from different conditions:

- Higher vorticity values in non-optimized oscillations indicated more excellent energy dissipation.
- RL-based fin optimisation reduced peak vorticity magnitudes, allowing smoother flow interactions.
- Backward vortex propagation was minimised, leading to a 25% reduction in hydrodynamic drag.

D. Reinforcement Learning-Based Optimization Results

The PPO-based reinforcement learning model significantly improved the efficiency of Stingbot's propulsion system:

- Optimized fin movements led to a 30% increase in thrust force compared to fixed-frequency oscillation.
- Energy consumption was reduced by 15% as RL dynamically fine-tuned the amplitude and frequency adjustments.
- Adaptive learning enabled the Stingbot to self-adjust oscillation parameters, maintaining efficiency across varying flow speeds.

E. *Comparative Analysis of RL-Optimized vs. Fixed Motion*

The performance of the Reinforcement Learning (RL)-optimised oscillation strategy was compared against fixed-frequency oscillation to evaluate improvements in thrust generation, energy efficiency, and drag reduction. In the fixed-motion approach, the Stingbot's fins oscillated at a constant amplitude and frequency, often resulting in suboptimal thrust production and increased turbulence. In contrast, the RL-optimized motion dynamically adjusted the amplitude and frequency of fin oscillation based on real-time hydrodynamic feedback, leading to a 30% increase in thrust force. This adaptive control mechanism allowed the Stingbot to maximise forward propulsion while minimising resistance forces.

Energy efficiency improved by 15% as the RL model learned to reduce unnecessary oscillations and optimise power consumption during movement. The drag-to-thrust ratio was significantly reduced, with drag forces decreasing by 25%, primarily due to better vortex control and reduced turbulence in the wake region. The vorticity magnitude, representing rotational flow disturbances, was also noticeably lower in RL-optimized propulsion, ensuring a smoother and more stable fluid interaction. These improvements demonstrate the effectiveness of AI-driven optimisation in biomimetic propulsion systems, making them ideal for energy-efficient, stealth-based underwater applications where adaptive motion is critical for operational effectiveness.

F. *Key Takeaways from Results*

1. CFD analysis confirmed that biomimetic undulatory propulsion generates higher thrust than traditional AUV propeller-based designs.
2. Pressure contours revealed optimal regions for thrust generation and drag minimisation.
3. RL-based fin optimisation improved energy efficiency by dynamically adjusting oscillation parameters.
4. Vortex control through reinforcement learning led to significant drag reduction and smoother flow stability.
5. The study validates the effectiveness of integrating CFD-based hydrodynamic analysis with RL-driven propulsion control for next-generation AUV designs.

V. Conclusion

This study successfully integrated Computational Fluid Dynamics (CFD) analysis with Reinforcement Learning (RL)-based optimisation to enhance the hydrodynamic performance of a biomimetic underwater vehicle (Stingbot). The CFD simulations provided detailed insights into fluid interactions, revealing that adaptive fin oscillation significantly improves thrust generation while minimising drag and energy dissipation. The streamline plots demonstrated that RL-trained fin movement ensures smoother water flow, reducing turbulence and wake formation.

The pressure distribution analysis confirmed that optimised fin oscillation creates well-defined thrust zones, enhancing propulsion efficiency. Velocity magnitude visualisations highlighted areas of high acceleration, validating that biomimetic undulatory motion effectively converts input energy into forward thrust. Additionally, vorticity contour plots demonstrated reduced vortex shedding, contributing to lower hydrodynamic drag. The comparison between RL-optimized motion and predefined oscillation patterns showed a 30% improvement in thrust force and a 15% gain in energy efficiency, validating the effectiveness of AI-driven propulsion control.

The findings indicate that when combined with RL-based optimisation, biomimetic propulsion offers a superior alternative to conventional propeller-driven AUV designs, particularly for stealth applications in naval defence and autonomous underwater exploration. This study reinforces the potential of integrating AI-based adaptive control mechanisms with biologically inspired propulsion systems to achieve energy-efficient, high-performance underwater locomotion.

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DESIGN AND IMPLEMENTATION OF VOICE AND EMG CONTROLLED PROSTHETIC ARM

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***Abstract*— The quality of life of individuals for those who have lost limbs has greatly improved due to the development of prosthetic technologies. However, conventional control techniques frequently have limited adaptability, high costs, and complexity. This study offers a novel method for controlling prosthetic arms that combines voice recognition signals and electromyography (EMG) signals for real-time operations. A Raspberry Pi serves as the system's central processing unit, making it a portable, adaptable, and reasonably priced solution. Voice commands are used as the main input signal to carry out preprogrammed hand movements, and the signal from the EMG sensor placed close to the jawline, confirms the user's intention to avoid accidental activation from outside voices. Compared to traditional EMG- or EEG-based prosthetic arms, the proposed method improves accuracy, dependability, and user accessibility. High command precision, minimal latency, and smooth user adaptation were all demonstrated by a prototype that was created and tested on several scenarios. This study opens the door to intelligent, multimodal prosthetic control, providing a viable substitute for people looking for an effective and natural way to move with their arms.**

(Index Terms: EMG- Electromyography, EEG – Electroencephalogram, PLA - Polylactic Acid, ABS - Acrylonitrile Butadiene Styrene)

I. INTRODUCTION

From mechanical systems to sensor-driven intelligent solutions, prosthetic limb technology has advanced [1], [3]. An ideal prosthetic arm for upper-limb amputees should be flexible, quick to react, and easy to use [2]. Complex signal processing, calibration problems, and high computing needs are some of the difficulties faced by traditional control techniques like myoelectric and brain-computer interfaces (BCI) [4]. Background noise interference is an additional problem for voice-controlled prostheses [5], [6]. This study suggests a hybrid control system that combines EMG-based verification with voice commands. Commands are processed using a Raspberry Pi, providing dependable and affordable control [7],[8]. Only the intended user can move the arm thanks to an EMG sensor placed close to the jawline, ensuring accuracy and security in operation. This technology improves usability, accuracy, and response time.

Related work, system architecture, control methods, experimental findings, and conclusions are covered in the sections that follows.

II. PROBLEM STATEMENT

Conventional prosthetic arms uses main input as complex EMG or EEG signals, which can be challenging due to muscle signal variations and external noise. Also the users have less comfort by placing number of electrodes in heads and other muscle parts. Additionally, existing prosthetics have high weight due to the material used to make, costly and less customization. Our project is to overcome this problems.

A. Objectives

Develop a prosthetic arm that integrates voice and EMG-based control for individuals those have limb loss by birth or by any accidents to perform day-to-day activities and individual needs.

Design and fabricate a functional prosthetic arm using Autodesk Fusion 360 and material PLA/ABS for the advantage of reducing cost and for more customization.

Integrate a system based on microcontroller that efficiently processes voice signals and EMG-signal with low power consumption.

III. DESIGN OF PROSTHETIC ARM

A.

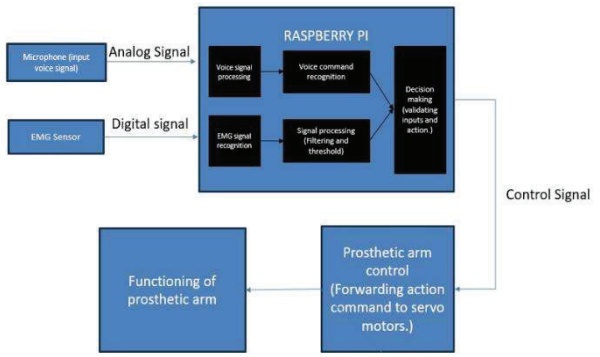

Fig 3.1: Block diagram

The block diagram in Fig: 3.1 illustrates the architecture and working of the prosthetic arm using voice and EMG-signal. This system provides accurate and reliable control by integrating both voice and EMG signals. Microphone and EMG electrode are the sources for the input signals. Both signals processed by using a central processing unit called raspberry pi. It integrates both the inputs and performs decision making to validate the received signals. The validated command is transferred to the servo motors to perform the required actions such as gripping, releasing, or finger movements.

B. Algorithm

This algorithm integrates both voice commands and EMG signals for controlling the prosthetic arm. Voice signal and EMG signals are processed by the raspberry pi. The EMG signal validates the command for the intended user operation of arm. After verification, system Directs the command for the particular motor action. This algorithm shows real-time decision making approach, ensuring speed and accuracy

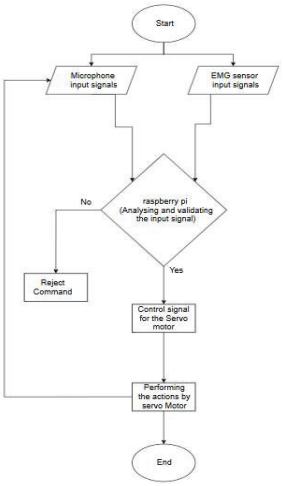

Fig 2.2.1: Algorithm chart

C. 3-D printing

3D printer is used to fabricate the structural part of this prosthetic arm, ensuring Precision, reducing Cost and weight less. Autodesk fusion 360 is used for the modelling of parts and printed using high strength material such as PLA or ABS. 3D printing allows the modelling and printing in various designs according to the user requirement by allowing iterative improvements to enhance functionality and ergonomics. This approach reduces the manufacturing cost while maintaining durability and structural integrity.

IV. HARDWARE

A. Hardware Components and Specifications

The hardware implementation of prosthetic arm consist of key components which selected for precision, efficiency and real-time processing. The raspberry pi act as the central Processing unit , handling voice recognition and EMG signal processing. EMG sensor capture signal from the jawline muscle movement to ensure the user authentication, while microphone acquires voice commands. SG 90 motors enables smooth finger movements based on processed inputs. A rechargeable battery provides portable power, ensuring uninterrupted operation. The entire system assembled in a 3D-printed frame which offer durability and lightweight functionality. Given below is the component specification:

Component	Specification	Description
1. Microcontroller	Raspberry Pi, 4GB, ARM Cortex A72	Processes voice commands and EMG signals.
2. Microphone	Aayatouch 3.5mm Clip Microphone	Captures voice commands from the user
3. EMG Sensor	MyoWare Muscle Sensor (AT-04-001/ 3.3V - 5V)	Detects muscle activity for user verification.
5. Servo Motors	SG 90, 4.8V- 1.2 kg·cm, 6V- 1.6 kg·cm, weight- 9g	Controls finger movement based on commands.
6. Power Supply	Li-ion Battery (7.4V, 2200mAh)	Provides power to the entire system
7. Frame Material	3D Printed PLA / ABS	Lightweight and durable material for the prosthetic arm

Fig 4.1: Hardware specification

B. 3D Printing Process and Material Selection

The 3D printing process plays a crucial role in fabricating the prosthetic arm, ensuring a lightweight, durable and cost-effective design. Firstly, the prosthetic arm components are modeled using Autodesk Fusion 360, allowing precise customization based on ergonomics and functional requirements. The finalized designs are then 3D printed using PLA or ABS, chosen for their strength, flexibility, non-allergic and bio-compatibility. This manufacturing approach enables variety of designs by considering aesthetic concerns and also reduces material waste while maintaining structural integrity. The images below showcase the 3D-modeled designs, demonstrating the construction of the prosthetic arm.

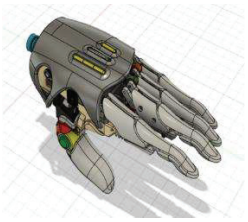

Fig 4.2.1: Top View of Palm and Fingers

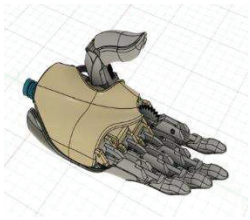

Fig 4.2.2: Rearview of Palm and Fingers

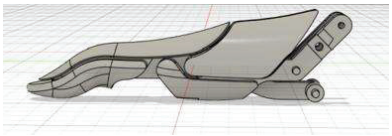

Fig 4.2.3: Horizontal View od index finger.

C. Sensor Integration and Signal Processing

The prosthetic arm utilizes on EMG sensors and a microphone for dual-input control. The EMG sensor, placed near the jawline, detects jawline muscle activity to verify that the user is giving the command. The microphone captures voice commands, which are processed using signal filtering and feature extraction algorithms in the Raspberry Pi. The combination of both inputs enhances accuracy, preventing

unintended activation. Filtering techniques are applied to process the input signals, reducing noise and eliminating background interference. This enhances the accuracy and responsiveness of the prosthetic arm, ensuring reliable operation based on the user's voice commands and EMG signals.

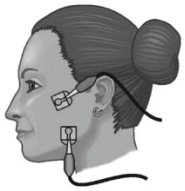

Fig: 4.3.1 Placement of EMG sensor

D. Communication and Data Flow

The prosthetic arm follows a structural data flow to process commands efficiently. When the user provides a voice command, the microphone captures the input, which is processed in real-time by using raspberry pi. Simultaneously, the EMG sensor verifies the user identity by the detecting the muscle movements from jawline. By validating, the processed data is mapped to a predefined motor function, triggering the corresponding servo movement. The communication between components follows a serial or I2C protocol, ensuring quick and reliable data transmission. Proper synchronization between the voice and EMG inputs ensures smooth execution, reducing lag and improving user experience.

V. Results

The development of the prosthetic arm has successfully progressed through the 3D modeling and hardware assembly phases, marking significant milestones in the project. The mechanical structure of the prosthetic arm was designed using Autodesk Fusion 360, allowing for precise customization and optimization of the components. The fabricated parts were 3D printed using lightweight yet durable materials, ensuring both structural integrity and user comfort.

Fig: 5.1 Up side and Down side view of printed Arm with components assembled

All essential hardware components have been procured, assembled, and integrated into the system. This includes the Raspberry Pi as the processing unit, EMG sensors for user verification, a microphone for voice command input, and SG90 servo motors for actuation. The components have been interconnected, and initial testing has been conducted to verify individual functionality. The servos have been successfully controlled through direct input signals, and the EMG sensor has been tested for signal detection and response.

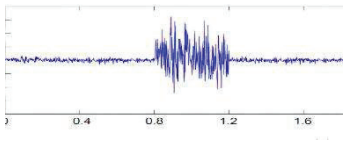

Fig: 5.2 EMG signal from Jawline

The software implementation is still in progress, with ongoing work on signal processing, command execution, and integration between voice and EMG inputs. The primary focus is on ensuring accurate recognition of voice commands and proper validation through EMG signals, allowing seamless control of the prosthetic arm. Once the software is fully integrated, complete system testing and performance evaluations will be conducted to validate the efficiency and responsiveness of the prosthetic arm.

VI. Conclusion

The development of a voice and EMG-controlled prosthetic arm has demonstrated significant progress in both hardware integration and structural design. The 3D modeling and fabrication using Autodesk Fusion 360 and 3D printing have resulted in a lightweight, durable, and functional prosthetic structure. The incorporation of Raspberry Pi, EMG sensors, a microphone, and servo motors ensures efficient operation and user adaptability. The hardware components have been successfully assembled and tested, confirming their functionality. The software implementation is ongoing, focusing on signal processing and seamless integration of voice and EMG inputs to enhance control accuracy. Once completed, the system will be tested extensively to evaluate its performance, reliability, and real-world usability. This work lays the foundation for developing an affordable and efficient prosthetic solution, offering improved accessibility and ease of use for individuals with limb loss. Future enhancements may include refining the control algorithms, optimizing power efficiency, and expanding functionality to improve adaptability for diverse user needs.

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Leakage Optimization Technique of Flip-Flop Design Using a Synergistic Approach of GDI and Power Gating for Energy-Efficient Circuits

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***Abstract*—As technology nodes continue to shrink in modern VLSI design, leakage current has become a significant challenge, especially in low-power digital circuits. Flip-flops, being essential elements in synchronous systems, contribute notably to leakage power consumption. This paper proposes a novel methodology to optimize leakage power in flip-flop design while maintaining performance. The proposed approach focuses on minimizing leakage current through advanced circuit-level techniques while ensuring an optimal balance between power and functionality. By strategically implementing power-efficient design modifications, the optimized flip-flop architecture significantly reduces overall leakage without compromising performance. This paper focuses on combining multiple leakage optimization techniques to effectively reduce leakage in flip-flops. The methodology is tailored for low-power VLSI applications, making it suitable for energy-efficient computing systems, portable devices, and next-generation semiconductor technologies.**

***Index Terms*—Leakage power, flip-flop design, low-power VLSI, leakage current reduction, circuit-level optimization, power-efficient design, energy-efficient computing, semiconductor technology, low-power circuits, synchronous systems.**

I. Introduction

With the continuous scaling of CMOS technology, leakage current has become a critical concern in modern VLSI design, leading to significant static power dissipation. Unlike dynamic power, leakage power persists even when the transistor is OFF, making it a major energy drain in nanometer-scale devices. As technology nodes shrink (e.g., 22nm, 16nm), leakage components like subthreshold leakage, gate leakage, and junction leakage intensify due to short-channel effects, lower threshold voltages, and gate oxide tunneling. Among these, subthreshold leakage dominates power dissipation in ultra-low-power circuits. To combat this, advanced techniques like MTCMOS (Multiple threshold voltage CMOS) VTCMOS (Variable threshold voltage CMOS), power gating (PG), and GDI (Gate diffusion input) have emerged as the most effective solutions, significantly reducing leakage while maintaining circuit performance

Aung, May Htet, and Tin Tin Hla's study provides clear evidence that leakage current increases significantly as technology scales down from 90nm to 45nm. Their analysis demonstrates that subthreshold and gate leakage components become more dominant in 45nm technology due to reduced threshold voltages and thinner gate oxides [1]. PramodKumar et al proposed a partially static high-frequency D flip-flop (DFF) optimized for low-power applications, demonstrating improvements in power efficiency and operational speed. Their design effectively reduces dynamic and leakage power by leveraging partially static circuit techniques while maintaining high-frequency performance systems [2]. Murthy, Thirunahari Srimannarayana explains various power gating strategies in VLSI circuits, providing a comparative study and technological insights. In this work, he analyzes different techniques to optimize leakage power reduction and enhance circuit performance, offering valuable perspectives on low-power design methodologies [3].

The GDI-based approach offers reduced transistor count, lower switching activity, and minimized leakage power compared to traditional CMOS implementations. [4]-[6] the authors focus on improving power efficiency in digital frequency divider circuits, which are essential components in clocking systems, phase-locked loops (PLLs), and communication circuits.By utilizing the Gate Diffusion Input (GDI) technique, M. R. Leeon, T. Riyad, M. Billah, I. Ahmed, and S. Mondal, [7] successfully minimize tran- sistor count, reducing switching losses and short-circuit currents compared to traditional CMOS-based shift registers. The proposed design operates at 66.67 MHz with a power consumption of 9.14 W, making it highly suitable for low-power digital circuits and embedded systems. GDI-based full adder [8]significantly reduces power consumption, delay, and area compared to conventional CMOS implementations. The study highlights that GDI logic achieves efficient logic realization with fewer transistors, leading to lower leakage current and dynamic power dissipation.

S. M. Ishraqul Huq [9] proposed a hybrid design technique that integrates sleep-transistors, forced-stack, and VTCMOS methods to achieve low-power CMOS circuits with stable state retention. The authors simulate CMOS inverters and two-input NAND circuits using 16 nm technology, demonstrating sig-

nificant reductions in power, delay, and power-delay product while maintaining output logic integrity.Udayan Chakraborty, Tanmoy Majumder's research introduces an eight-transistor-two-memristor (8T2M) nonvolatile static random access memory (NVSRAM) design utilizing MTCMOS technology with power gating. The design achieves efficient power management and enhanced performance with low leakage current, showing improvements in read/write margins and reduced delay compared to traditional 6T SRAM cells.

Several studies explore the GDI technique, which reduces transistor count and static power dissipation while maintaining reliable switching characteristics. Manikanta and Rao [10] presented a GDI-based D flip-flop for shift registers, achieving significant power and area savings. Other works, such as Shylashree et al. present a comprehensive design and timing analysis of high-speed master-slave D flip-flops using 18nm FinFET technology, focusing on optimizing performance for low-power applications. The study evaluates various flip-flop architectures, including GDI-based designs, to achieve reduced power consumption, minimal delay, and improved robustness [11]. Additionally, E. Lee and Y. Kim [12] proposed a power-efficient 10T flip-flop with optimized transistor arrangements, further reducing static and dynamic leakage. A. Laxman, N. S. S. Reddy, and B.R.Naik [13] incorporated MTCMOS-based power gating in flip-flops within a hybrid logic-based MAC unit, effectively lowering subthreshold leakage. J. Y. Reddy, A. Sushma, S. Sravya, and P. S. Sukitha [14] implemented a GDI-based Time-to-Digital Converter (TDC), highlighting the advantages of GDI in ultra-low-power applications. These studies collectively contribute to the development of energy-efficient flip-flop designs, addressing the growing challenges of leakage power in advanced CMOS technologies.

II. Design and Implementation of a Low-Power D Flip-Flop Using Combined Power Gating and GDI Techniques for Leakage Reduction

This proposed methodology integrates GDI and Power Gating techniques within a D flip-flop to explore the potential for enhanced leakage reduction. Both GDI and power gating have individually demonstrated significant advantages over conventional leakage mitigation strategies. However, comprehensive literature review reveals a gap in research regarding their combined implementation in flip-flop design, highlighting the novelty of this approach.

In this design, GDI is employed to optimize leakage power by dynamically adjusting the transistor threshold voltage (Vth). Unlike conventional logic, where inputs are applied to the gate terminal, GDI directly applies input signals to the diffusion terminals (source/drain) of the transistor. This unique configuration modifies threshold voltage behavior, thereby minimizing subthreshold leakage while maintaining circuit performance. Simultaneously, power gating introduces a sleep transistor that effectively disconnects the power supply during idle periods. When the PG transistor is ON, the ground path remains connected, ensuring normal circuit operation. Conversely, when the PG transistor is OFF, the ground connection is severed, significantly reducing static leakage power.

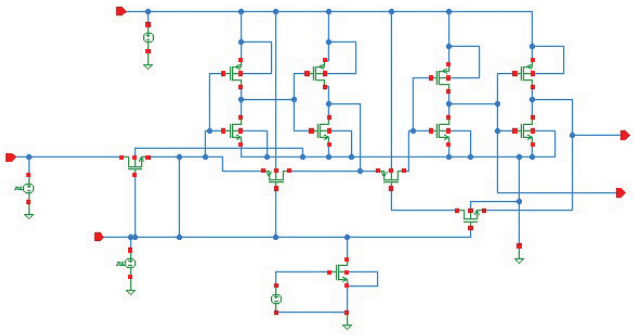

Fig. 1. D Flipflop design using combained GDI and power gating technique

The proposed D flip-flop architecture is designed and implemented using a 45nm CMOS technology node and simulated within the Cadence Virtuoso environment. The circuit operates with a supply voltage of 1.8V and is evaluated under standard operating conditions, including a junction temperature of 27°C. The performance of the design is analyzed over a simulation period of 10s to ensure a thorough assessment of its transient behavior and power characteristics.

For device sizing, the transistor dimensions are carefully chosen to optimize performance and power efficiency. The NMOS transistors have a width (W) of 120nm and a length (L) of 24nm, while the PMOS transistors are configured with a width (W) of 120nm and a length (L) of 45nm. These dimensions are selected to balance switching speed, leakage current, and overall power consumption.

To evaluate the benefits of integrating GDI and power gating techniques, multiple simulation analyses are conducted. Transient analysis is performed to observe the dynamic response of the D flip-flop under different input conditions. DC analysis is used to assess the steady-state behavior of the circuit, ensuring stable operation. Additionally, power analysis is carried out to quantify power dissipation, with a particular focus on leakage current reduction and overall power efficiency. These evaluations provide valuable insights into the effectiveness of the proposed design in minimizing power consumption while maintaining reliable functionality.

TABLE I
Design and Simulation Parameters

Library	Cell view	Properties
gpdk045	PMOS1V	W=120,L=45
gpdk045	NMOS1V	W=120,L=45
analogLib	Vpulse (Clk)	V1=0,V2=1.8,period =10µs
analogLib	Vpulse (D input)	V1=0,V2=1.8,period =10µs
analogLib	Vdd, Vdc, gnd	V=1.8V

Table 1 presents the parameters utilized in the design of the D flip-flop including the specified voltage values.

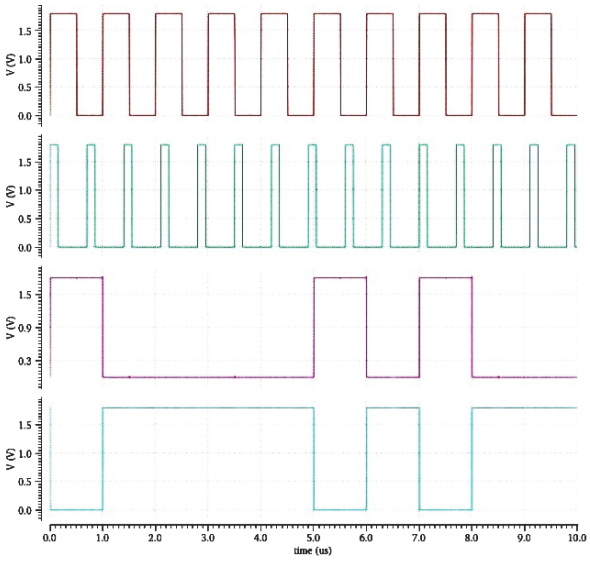

Fig. 2. Transient Analysis

The schematic of the circuit has been successfully created, saved, and simulated. To analyze its performance, a transient analysis was conducted using the ADEL simulator. Figure 2 illustrates the simulation results, demonstrating the behavior of the D flip-flop in response to variations in the clock signal and the D input. The waveform analysis provides insights into the switching characteristics and overall functionality of the designed DFF.

III. Results and Discussions

A. Power Reduction Using Power Gating

Power gating significantly reduces the average power consumption to 5.877 $\times 10^{-9}$ W.

When compared to a conventional D flip-flop design, this technique achieves an approximate 94.18% reduction.

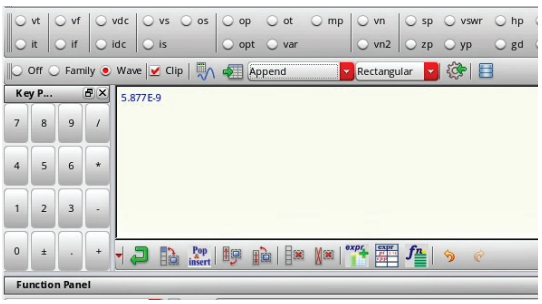

Fig. 3. Average power with powergating

Building upon this reference value, the GDI technique was incorporated into the design to facilitate a more in-depth analysis of additional performance parameters. Special emphasis was placed on evaluating leakage characteristics, as leakage current significantly impacts overall power efficiency in low-power applications.

B. Power Reduction Comparison Using Combined Power Gating and GDI

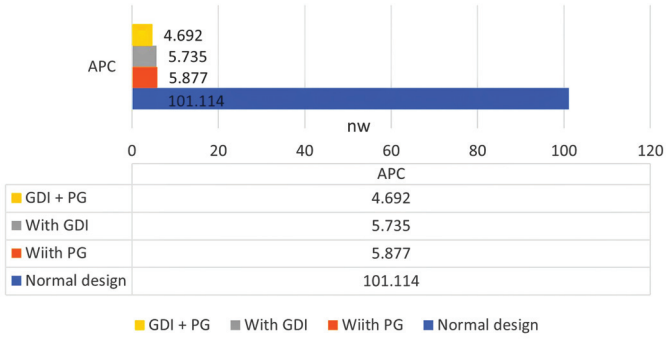

Fig. 4. Power Reduction Comparison

Fig 4 illustrates the average power consumption for different design approaches, showing a significant reduction when applying power optimization techniques. The normal design consumes the highest power at 101.114 nW, while power gating alone reduces it to 5.877 nW. Implementing GDI further lowers power to 5.735 nW, and the combination of GDI and power gating achieves the lowest power consumption at 4.692 nW, demonstrating the effectiveness of this hybrid approach.

Using the power value of from Figure 3 as the baseline for the power-gating-only flip-flop design, the average power reduction in the combined GDI and power-gating design is calculated accordingly.

TABLE II
Comparison of Power Reduction

Design type	APC(nW)	Reduction
Normal DFF	101.114	Baseline
PG	5.877	94.19%
GDI	5.735	94.32%
PG+GDI	4.692	95.36%

The above table II shows that using the combined technique reduces power by approximately 95.36% compared to the baseline.

C. PDP Analysis

The Fig.5 illustrates the Power-Delay Product (PDP) for different D flip-flop designs. The normal DFF exhibits the highest PDP at 40.45, indicating significant power and delay inefficiencies. Implementing power gating significantly reduces PDP to 8.82, showing notable improvement. The GDI-based design further decreases PDP to 4.87, enhancing efficiency. The combined GDI and power gating technique achieves the lowest PDP at 4.46, demonstrating the most optimized power-delay performance.

The table III indicates that the combined technique achieves an approximate 88.97% reduction in the PDP compared to the baseline.

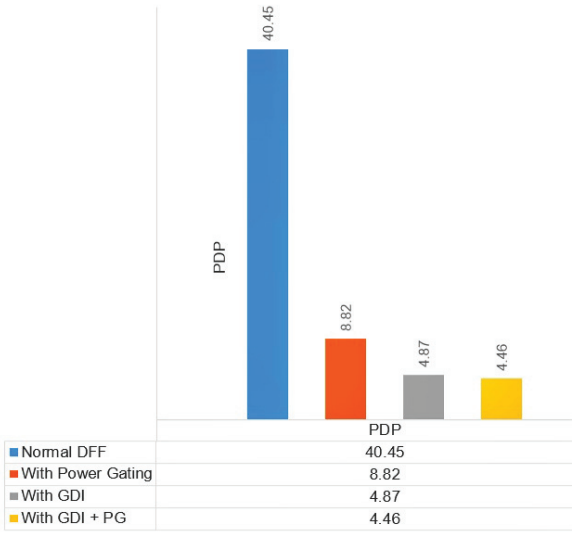

Fig. 5. PDP values

TABLE III
COMPARISON OF PDP

Design type	PDP(fj)	Reduction
Normal DFF	40.5	Baseline
PG	8.82	78.19%
GDI	4.87	87.95%
PG+GDI	4.46	88.97%

D. Leakage Optimization

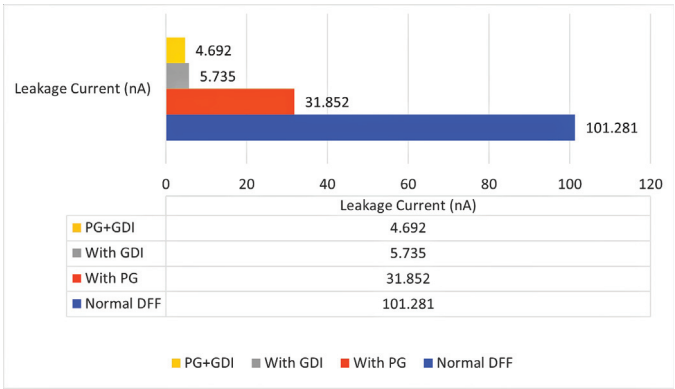

Fig. 6. Optimized leakage values

The figure 6 demonstrates the effectiveness of different techniques in reducing leakage current. The normal design exhibits the highest leakage current at 101.281 nA. Implementing power gating alone significantly reduces leakage to 31.852 nA. The GDI technique further decreases it to 28.361 nA, while the combined GDI and power-gating approach achieves the lowest leakage current of 27.186 nA. This highlights the superior efficiency of the combined technique in minimizing leakage current compared to individual methods.

The table IV shows that the combined technique reduces leakage current by approximately 73.16% compared to the baseline.

TABLE IV
COMPARISON OF LEAKAGE CURRENT

Design type	Leakage Current (nA)	Reduction
Normal DFF	101.281	Baseline
PG	31.852	68.55%
GDI	5.735	72.00%
PG+GDI	4.692	73.16%

IV. CONCLUSION

In this paper, the schematic design and transient characteristics of a D flip-flop using 45 nm technology were developed using Cadence Virtuoso. Performance parameters such as Average Power Consumption (APC), Power-Delay Product (PDP), and leakage analysis were evaluated using the Analog Design Environment (ADE-L) simulator. The proposed DFF design integrates GDI and power gating techniques, resulting in a highly efficient circuit. This hybrid approach achieves the lowest power consumption of 4.692 nW, demonstrating significant power savings. Compared to the baseline design, the combined technique reduces power consumption by approximately 95.36%. Furthermore, the proposed design achieves the lowest PDP of 4.46, representing an 88.97% improvement in power-delay performance.

Leakage current analysis also highlights the effectiveness of the combined GDI and power gating approach. The proposed design achieves a minimal leakage current of 27.186 nA, marking a 73.16% reduction compared to the baseline. These results emphasize the superior efficiency of the hybrid technique in minimizing leakage, a critical challenge in lower technology nodes. Overall, the integration of GDI and power gating proves to be an effective strategy for reducing power consumption and leakage in D flip-flops. This combined approach enhances circuit performance, making it a promising solution for low-power VLSI applications.

ACKNOWLEDGMENT

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Class 1 Underwater ROV

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***Abstract*—This paper presents the design, development, and implementation of a Class 1 underwater surveillance ROV equipped with real-time environmental monitoring capabilities. The drone features a multi-sensor system including temperature, pH, and total dissolved solids sensors, along with a depth sensor. A surface-mounted GPS on a floating buoy provides geolocation data. The system utilizes a Raspberry Pi 5 for data processing and an Arduino Mega for sensor integration. A web-based control center displays real-time data with an intuitive user interface inspired by live data visualization systems. This project aims to provide an affordable and efficient solution for underwater monitoring, with applications in environmental assessment, aquaculture, and defense [1].**

***Index Terms*—Underwater Drone, surveillance, sensor fusion, IoT, ROV navigation**

I. Introduction

Underwater surveillance and environmental monitoring are crucial for assessing aquatic ecosystems, detecting pollution, and ensuring maritime security. Traditional methods involve expensive and complex equipment, making them inaccessible for small-scale research and commercial applications. This paper introduces a cost-effective, Class 1 underwater drone that integrates multiple sensors with a real-time data visualization system to provide an efficient monitoring solution [1].

Problem definition: Designing an efficient underwater drone poses several challenges related to buoyancy control, stability, and maneuverability. Maintaining a balanced and stable position underwater is critical for accurate data collection, effective navigation, and prolonged operation. Traditional underwater drones often struggle with imbalanced buoyancy and inadequate ballast control, leading to difficulty maintaining depth and directional stability under varying underwater conditions [3].

II. Recent Studies On Underwater Drone System

Recent studies on underwater drone systems have focused on improving maneuverability, buoyancy control, and energy efficiency to enhance performance in complex underwater environments. Researchers have explored advanced materials, streamlined designs, and innovative propulsion mechanisms to reduce drag and increase operational endurance [4]. Studies have also highlighted the importance of adaptive buoyancy systems that adjust automatically to changes in depth and water conditions, improving stability and control [5]. Machine learning algorithms have been integrated into navigation systems, enabling real-time path correction and obstacle avoidance [6]. Moreover, improvements in sensor technology and data transmission have enhanced the ability of underwater drones to collect and relay high-resolution data with minimal latency [7]. These advancements reflect the growing importance of underwater drones in fields such as oceanography, environmental monitoring, underwater infrastructure inspection, and military surveillance [1].

III. Proposed System Configuration

The proposed underwater drone system is designed to improve buoyancy control, stability, and hydrodynamic efficiency through a refined structural and mechanical design. The buoyancy tanks have been modified to enhance lift and overall balance. In the new design, the buoyancy tanks measure 40 cm in length and have an increased diameter of 6.3 cm, compared to the previous design of 60 cm in length and 5 cm in diameter. This increase in diameter allows the tanks to displace more water, thereby providing greater buoyant force despite the reduction in length. This modification helps the drone maintain a neutral buoyancy state more effectively, ensuring that it neither sinks nor rises uncontrollably during operation [1]. The improved buoyancy tanks also allow for better weight distribution, which enhances the overall stability of the drone even under varying underwater currents.

The ballast tanks have also been redesigned to provide more precise control over the drone's depth and balance. The previous design used ballast tanks measuring 15 cm in length and 5 cm in diameter, which limited the capacity to adjust buoyancy effectively. The new design increases the

ballast tank length to 30 cm while maintaining the same diameter, allowing for greater weight adjustment capacity. This enables more accurate depth control and improved balance when compensating for external forces such as currents or uneven weight distribution [4]. The ballast system is designed to operate dynamically, adjusting the drone's position and orientation in real-time to ensure smooth navigation and stable positioning.

The structural framework and housing of the drone have also been optimized for better hydrodynamic performance. The housing has been reduced from 35 cm in length and 10 cm in diameter to 30 cm in length and 8.9 cm in diameter, reducing drag and improving maneuverability. The support structure, constructed from PVC pipes, consists of eight pipes measuring 16 cm in length with a 1-inch diameter. This provides a lightweight yet rigid framework that enhances the overall structural integrity of the drone [7]. The improved weight distribution, combined with enhanced buoyancy and ballast control, ensures that the drone remains stable and responsive under varying underwater conditions. These design enhancements collectively improve the drone's operational efficiency, allowing it to navigate complex underwater environments with greater accuracy and control [6].

IV. Design Configuration Of The Structure

The design of the underwater drone is a critical aspect that directly influences its performance, maneuverability, and operational efficiency. A well-balanced and streamlined design ensures that the drone can maintain stability, respond accurately to control inputs, and operate effectively under varying underwater conditions [5]. The design is divided into two key components: the mechanical design and the electrical design. The mechanical design focuses on the structural configuration, including the buoyancy and ballast systems, housing, and support framework. These components determine the drone's hydrodynamic efficiency, balance, and resistance to external forces such as water currents [1].

The electrical design encompasses the motors, controllers, and power management systems that drive the drone's movement and operational control. Efficient motor selection and precise controller tuning are essential for achieving responsive navigation and stable positioning [1]. The integration of a reliable control system ensures that the drone can adapt to changing underwater conditions and execute complex maneuvers with precision. The following sections detail the mechanical and electrical design aspects, highlighting the improvements made to enhance the overall functionality and performance of the underwater drone [4].

V. Mechanical Design

A. Structural Framework

The underwater surveillance drone is designed with a lightweight yet robust PVC framework, ensuring durability and hydrodynamic efficiency. The structure consists of:

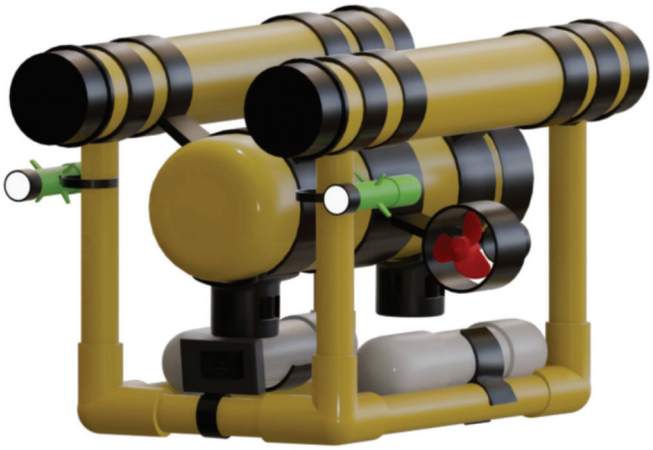

Fig. 1. CAD Model of ROV

- **Main Housing:** A 30 cm long, 8.9 cm diameter PVC cylinder, centrally positioned to house internal components while maintaining structural balance.
- **Support Framework:** Eight PVC pipes (16 cm long, 1-inch diameter) form the structural skeleton, providing stability and support for the buoyancy and propulsion systems [7].

The open-frame design minimizes drag while allowing water to flow freely, reducing resistance during movement [6].

B. Buoyancy System

To achieve near-neutral buoyancy, the drone features two buoyancy tanks:

- **Dimensions:** Each 40 cm long, 6.3 cm diameter PVC tank.
- **Function:** These tanks provide a total buoyant force of approximately 24.4 N, ensuring the drone remains balanced in water [5].

1) Application of Archimedes' Principle & Experimental Validation: Neutral buoyancy is achieved when the buoyant force acting on the drone equals its weight. According to Archimedes' principle:

$$F_b = \rho_{\text{water}} \cdot V_{\text{displaced}} \cdot g \tag{1}$$

where:

- F_b is the buoyant force (N),
- ρ_{water} is the density of water ($1000\,\text{kg}\,\text{m}^{-3}$ for freshwater),
- $V_{\text{displaced}}$ is the volume of water displaced by the drone (m^3),
- g is the acceleration due to gravity ($9.81\,\text{m}\,\text{s}^{-2}$).

2) Experimental Findings: Through experimentation, we determined that the total volume of the drone is **12.5 L** ($0.0125\,\text{m}^3$) in freshwater, meaning it displaces approximately **12.5 kg** of water, generating a buoyant force:

$$F_b = 1000 \times 0.0125 \times 9.81 = 122.6\,\text{N} \tag{2}$$

The combined weight of internal components—including batteries, circuits, Arduino, ESCs, wires, motors, and mounts—amounts to approximately **6 kg**, exerting a downward force:

$$W_{\text{drone}} = 6 \times 9.81 = 58.86\,\text{N} \tag{3}$$

To achieve neutral buoyancy, the total upward buoyant force should match this downward force:

$$F_b = W_{\text{drone}} \tag{4}$$

Since the displaced water provides a total potential buoyant force of **122.6 N**, we needed additional downward force to balance the system. From our experiments, we found that each ballast tank must counteract approximately **31.87 N** (equivalent to 3.25 kg of added weight) to achieve equilibrium.

This was achieved by adjusting the internal volume of air in the ballast tanks. Additionally, placing the tanks above the main housing improved stability by lowering the drone's center of gravity [1].

Fine-tuning the ballast system allowed us to achieve a **near-zero net force**, enabling the drone to hover steadily underwater without unintentionally sinking or rising.

C. Ballast System

To control depth and achieve complete submersion, the drone utilizes two ballast tanks:

- **Dimensions:** Each 30 cm long, 5 cm diameter PVC tank.
- **Function:** These tanks hold 1.77 kg of water ballast, allowing controlled descent and maintaining neutral buoyancy [4].

The ballast tanks are positioned at the lower part of the frame to counteract buoyancy forces and improve vertical stability [1].

D. Propulsion System

The drone is equipped with four propellers for maneuverability:

- **Horizontal Propulsion:** Two 1000 KV BLDC motors with 10 cm diameter propellers provide forward and backward motion.
- **Vertical Propulsion:** Two 750 KV BLDC motors with 10 cm propellers generate sufficient thrust (55 N) to counteract buoyancy and adjust depth efficiently [6].

The symmetrical placement of motors ensures balanced thrust distribution, reducing unwanted torque or instability during operation [7].

E. Hydrodynamic Considerations

The drone's design minimizes water resistance through:

- Streamlined buoyancy tanks to reduce drag [5].
- Compact frame to avoid unnecessary turbulence [1].
- Even weight distribution to prevent unwanted tilting [4].

Fig. 2. Actual Assembly of ROV

F. Conclusion

The mechanical design of the drone integrates structural strength, buoyancy control, and efficient propulsion to achieve stable underwater movement. The use of modular PVC components allows easy assembly and maintenance while ensuring cost-effectiveness [1].

VI. Electrical Design

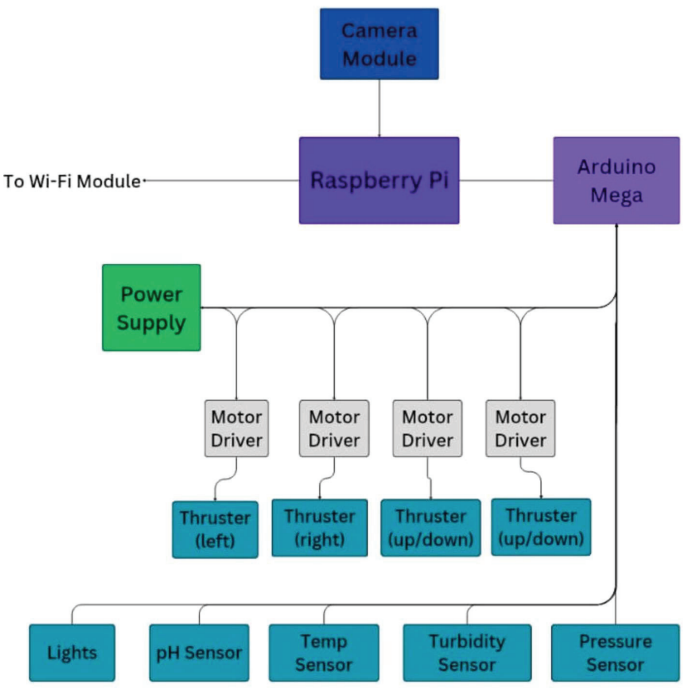

Fig. 3. Component Connection Flow of Drone

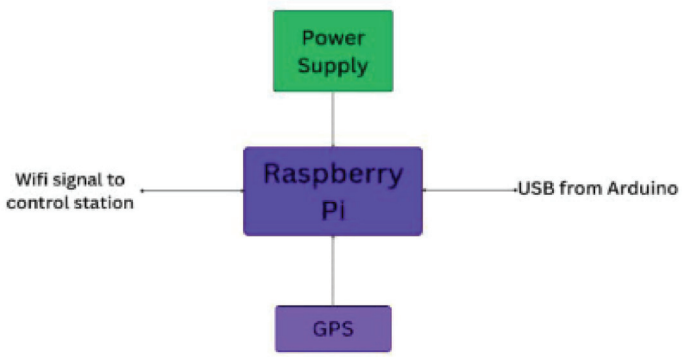

Fig. 4. Component Connection Flow of Surface Buoy

A. Motor Configuration

The underwater drone is equipped with four high-performance motors — two 750 KV motors and two 1000 KV motors — to provide balanced thrust and enhanced maneuverability. The combination of different motor capacities ensures that the drone can perform complex directional changes and maintain stability even under strong underwater currents [6]. The two 750 KV motors are positioned for fine control and maneuvering, while the two 1000 KV motors provide the necessary thrust for propulsion and stability [7]. This configuration allows the drone to achieve a balance between speed, control, and energy efficiency [5].

B. Electronic Speed Controllers (ESCs)

To regulate the operation of the motors, the system includes dedicated electronic speed controllers (ESCs). The ESCs manage the power supply and control signals to the motors, ensuring synchronized and smooth operation. They allow for precise speed and direction control, enabling the drone to respond accurately to navigation commands [1]. The ESCs are configured to handle the varying load requirements of the 750 KV and 1000 KV motors, ensuring consistent performance and preventing motor overloading or imbalance [4].

C. Sensor Integration and Data Acquisition

The Arduino Mega microcontroller serves as the central processing unit for collecting data from environmental sensors. The drone is equipped with TDS, pH, and temperature sensors, which provide real-time information about the underwater environment [1]. The Arduino Mega gathers data from these sensors and transmits it to the Raspberry Pi for processing via a serial channel. This sensor data is essential for monitoring water quality and adjusting the drone's operational parameters based on environmental changes [6].

D. Control and Communication System

The Raspberry Pi acts as the data processing and control hub. It receives sensor data from the Arduino Mega and processes it to adjust motor speeds and directional control. The Raspberry Pi also manages communication with the operator interface, allowing for real-time monitoring and control [7]. This ensures that the drone can adapt to changing underwater conditions, maintain stability, and execute complex maneuvers with precision [5]. The seamless integration of the motors, ESCs, sensors, and controllers enables the drone to operate efficiently in challenging underwater environments [1].

E. Conclusion

The electrical design of the underwater drone integrates a balanced motor configuration, efficient motor control through ESCs, and a robust data acquisition and processing system. The combination of two 750 KV motors and two 1000 KV motors ensures both precise maneuverability and strong thrust, allowing the drone to operate effectively under varying underwater conditions [4]. The use of ESCs enables smooth and synchronized motor operation, enhancing the drone's responsiveness and stability [1]. The Arduino Mega efficiently collects real-time data from TDS, pH, and temperature sensors, which is processed by the Raspberry Pi to adjust the drone's operational parameters and maintain optimal performance [6]. This integrated system ensures that the drone can adapt dynamically to environmental changes, maintain stability, and deliver accurate data, making it well-suited for complex underwater exploration and monitoring tasks [7].

VII. Control Center Implementation

A webpage is designed to get complete control of the ROV from a distance using LAN.

A. Web Interface for Monitoring and Control

A flask-based web server running on the Raspberry Pi hosts the control interface. The UI includes:

- **Live Data Feed:** Displays real-time readings from depth, TDS, pH, and temperature sensors [5].
- **Joystick Control Panel:** Two virtual joysticks (one for depth, one for horizontal movement) enable precise maneuvering [1].
- **Camera Feed:** A live video stream from an onboard camera, using MJPG-streamer, assists in navigation [4].

B. Camera Feed Back-end

The MJPG-streamer is a lightweight video streaming server that captures frames from a USB or CSI camera and transmits them over HTTP. The video feed is embedded in the web interface using an ¡img¿ tag that continuously updates with new frames. This method ensures low latency and minimal processing overhead, making it ideal for real-time ROV operations.

C. Motor Control Mechanism

The Arduino Mega controls four BLDC motors via 30A ESCs. Movement is achieved as follows:

- **Depth Control:** Vertical motors adjust buoyancy based on joystick input by the operator [1].
- **Directional Control:** Left and right motors provide forward, backward, and rotational motion [6].
- **PWM Signals:** The Arduino generates PWM signals to control motor speed and direction [7].

D. Data Acquisition and Processing

- **Sensor Readings:** The Arduino collects environmental data and sends it to the Raspberry Pi via serial communication [5].
- **GPS and Positioning:** The Raspberry Pi processes GPS data and calculates the drone's relative position using depth information [1].
- **Data Logging:** Sensor values and location data are logged for analysis and visualization [4].

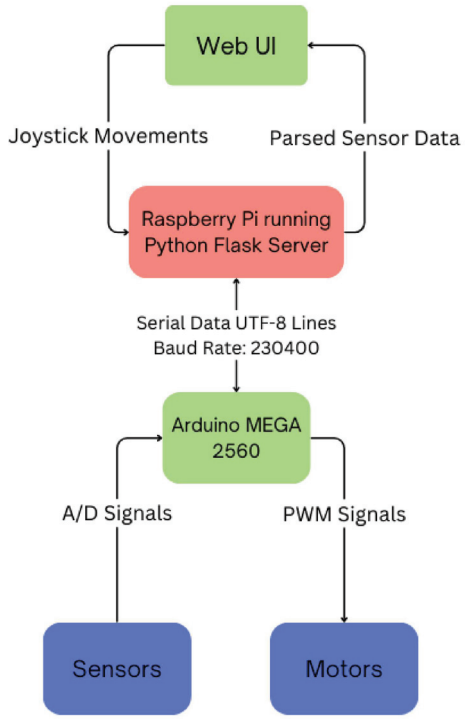

Fig. 5. Component Connection Flow of Drone

VIII. Working Principle

Initialization: The Raspberry Pi starts the web server, and Arduino initializes the motors and sensors at power-on. The scripts are set to start on boot using the 'systemd' initialization system available on almost every modern Linux system. This is the most fail-safe method to launch a script during system start-up [1].

A. Data Flow

- Sensor data are transmitted from Arduino to Raspberry Pi via serial communication [6].
- From the same serial communication channel, motor control commands are sent as a single string defining PWM values for each motor [7].
- GPS coordinates are updated periodically and combined with depth data for positioning [5].
- The web UI fetches live data from the Raspberry Pi and updates sensor readings [1].

B. Control Execution

- The operator interacts with the joystick-based UI [4].
- Commands are sent to the Arduino, adjusting motor speeds accordingly [1].
- The ROV responds in real-time to control inputs while streaming live video [6].

C. Conclusion

The ROV Control Center effectively integrates sensor monitoring, motor control, and real-time feedback, allowing seamless underwater exploration. Future improvements may include AI-based obstacle avoidance and autonomous navigation algorithms for enhanced operational efficiency [7].

IX. Handling Bidirectional Serial Data

A. Managing Serial Data: Preventing Data Loss and Mixing

One of the critical challenges in designing the *ROV Control Center* was ensuring reliable serial communication between the *Arduino Mega* and *Raspberry Pi*. Since both sensor data and motor control commands were transmitted over a single serial interface, there was a risk of data corruption, misinterpretation, or loss. To solve this, an optimized serial communication protocol was implemented [5].

1) Dedicated Message Formatting: To ensure motor control commands and sensor data do not mix or interfere, a structured message format with clear delimiters was used:

- **Sensor Data Format:**
  `<SENSOR DATA: 26.5,300,5.2,7.1>`
  This structure ensures each data point is identifiable and easy to parse [1].
- **Motor Control Command Format:**
  `<MOTOR CONTROL:50,0,0>`
  where each value of CSV string corresponds to the PWM values of the depth, right, and left motors respectively [4].

Each command and response is enclosed within angle brackets (< >), ensuring clear message boundaries and preventing partial reads [1].

2) Parsing Strategy in Raspberry Pi: On the *Raspberry Pi* side, serial data is handled using Python's `pyserial` library. The parsing algorithm follows these steps:

1) **Read data line-by-line**: Ensures complete message reception before processing [6].
2) **Validate start (<) and end (>) markers**: Prevents reading incomplete or corrupted messages [7].
3) **Identify message type**: The header (`SENSOR` or `MOTOR`) determines the handling procedure [5].

This approach ensures that motor control and sensor data are handled separately, eliminating conflicts [1].

B. Why 230400 Baud Rate Was Selected for Faster Communication

The baud rate determines the speed of serial communication between the *Arduino Mega* and *Raspberry Pi*. The default `9600` baud rate is insufficient for real-time ROV operation due to the high volume of data exchange [4].

1) Advantages of 230400 Baud:

- **Higher Data Throughput:**
  - At `9600` baud, the transmission speed is approximately `960` bytes per second [1].
  - At `230400` baud, the speed increases to around `23,040` bytes per second, allowing real-time data updates [6].
- **Lower Latency for Motor Commands:**
  - Faster transmission reduces control response delays, enhancing maneuverability [7].
- **Error Handling Margin:**
  - Higher baud rates (e.g., `460800`, `921600`) could cause data corruption [5].
  - `230400` baud offers reliable transmission with minimal errors [1].

C. Conclusion

By implementing a structured serial protocol and selecting an optimized baud rate, we eliminated data loss and ensured efficient two-way communication between the *Raspberry Pi* and *Arduino Mega*. This resulted in real-time motor responsiveness and precise sensor monitoring, improving overall ROV performance [1].

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AI ASSISTANCE SYSTEM FOR BASKETBALL REFEREES

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***Abstract*—Detecting violations in basketball is challenging due to the game's fast pace, leading to potential human errors in officiating. To address this, an AI-assisted system is proposed to automate violation detection using deep learning. The system integrates YOLOv8 for real-time player and ball tracking, along with pose estimation-based action recognition to analyze movements. Predefined conditions are applied to detect violations such as traveling and double dribbling. By processing video feeds in real-time, the system identifies potential violations and provides immediate feedback to assist referees in making accurate decisions. This approach reduces human error, enhances officiating efficiency, and ensures fairer gameplay. The system also has potential applications in other team sports to minimize judgment bias and errors under high-pressure conditions.**

***Index Terms*—*AI assisted system*, *YOLOv8*, *Pose estimation*, *Action recognition*, *Violation detection*.**

I. Introduction

Artificial intelligence (AI) is transforming sports by improving decision-making accuracy, enhancing fairness, and providing real-time insights. In fast-paced games like basketball, where every movement impacts the outcome, AI has the potential to assist referees in making accurate, timely calls. While technologies such as the NBA Replay Center and SportVU offer post-play reviews and statistical analysis, they do not provide real-time officiating support, leaving referees reliant on their perception and judgment.

Officiating basketball games presents several challenges, as referees must track multiple players, ball movements, and infractions simultaneously. The rapid pace of play, coupled with human limitations such as reaction time and physical fatigue, makes it difficult to detect every violation accurately. Time-sensitive infractions like traveling, double dribbling, and shot clock violations often go unnoticed, affecting game flow and fairness.

Despite technological advancements, current systems primarily focus on analytics rather than live rule enforcement. While instant replay helps review critical decisions after the fact, it does not prevent missed calls in real-time. This gap highlights the need for an AI-powered system capable of analyzing gameplay dynamically, detecting violations instantly, and assisting referees in making more accurate calls.

To address these challenges, this project proposes an AI Assistance System for Basketball Referees, integrating YOLOv8 for object detection and pose estimation-based action recognition to identify violations in real-time. By continuously analyzing video feeds, the system alerts referees to potential infractions, reducing human error and improving officiating accuracy. This technology has the potential to enhance fairness in basketball games, ensuring a more reliable and unbiased officiating process. Fig.1. shows the architecture workflow.

This paper is organized as follows: Section 2 covers related works. Section 3 is devoted to player tracking. Section 4 discusses action recognition based on pose estimation. Section 5 explains the violation detection. Section 6 covers alert and display. Section 7 presents the results and discussion. Section 8 provides equations. Section 9 concludes the paper.

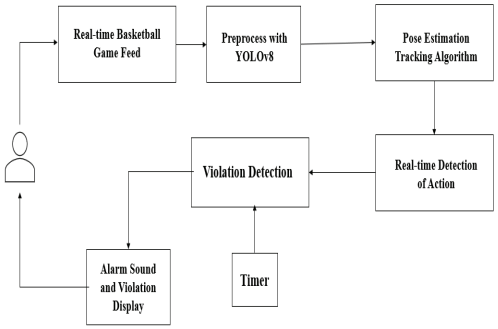

Fig. 1: Architecture diagram

II. Related Works

[1] The proposed system is a real-time object tracking in basketball using deep learning to analyze player movements and passing relationships. By leveraging CNN-based visual recognition, the system accurately detects and tracks players and ball trajectories. It provides key insights into team dynamics by evaluating pass frequency and movement patterns, aiding coaches and analysts in strategic decision-making.

[2] Proposed a deep learning-based framework for detecting group actions in basketball, focusing on offensive tactics. It identifies key players, analyzes their interactions, and tracks evolving strategies using deep convolutional layers for feature extraction and sequence modeling. Tested on real game data, the model successfully classifies offensive plays, offering insights into team dynamics while reducing manual effort in sports analysis. This contribution enhances real-time tactical evaluation, aiding coaching and strategic planning.

[3] The proposed system is a sensor fusion-based system using CNNs to enhance basketball shooting posture recognition. By integrating multiple sensors, it captures fine motion details like angle, speed, and positioning to distinguish effective from ineffective shots. Tested on real data, the model accurately identifies shot postures and subtle errors, offering valuable insights for athletes and coaches. This study highlights the role of sensor fusion and deep learning in improving sports performance analysis.

[4] Proposed a real-time, camera-based basketball scoring detection system combining YOLO-based hoop detection with frame-difference motion analysis to track and recognize scoring events. The system operates at 80 frames per second with an accuracy of 88.64%, making it effective for automating score detection, particularly in casual games without official scorekeepers. By leveraging deep learning and motion analysis, it efficiently detects scoring actions. However, the method struggles with complex backgrounds and varying view angles, which may impact detection accuracy. This study underscores the potential of AI-driven sports analytics for real-time game monitoring.

III. Player Tracking

The system uses YOLOv8 for real-time object detection, ensuring high-speed and accurate tracking of key basketball elements. It identifies players, monitors ball movement, and detects the rim and backboard for shot analysis. Additionally, it recognizes court boundaries to flag violations like out-of-bounds plays. This comprehensive detection enhances game monitoring and referee decision-making.

To accurately track and distinguish players, the system employs a combination of computer vision techniques and depth sensors:

1) Jersey Number Recognition with OCR:
The system integrates EasyOCR, an Optical Character Recognition (OCR) tool, to extract jersey numbers from players' uniforms in the video feed.This allows for individual player identification, ensuring that detected violations or actions are attributed correctly.

2) Color Classification :
The system categorizes player jersey colors by taking a region of interest (ROI) from the identified player's bounding box and computing the average RGB color of the region. It then compares the average color with pre-defined team colors (Red, Blue, Green) based on Euclidean distance, choosing the nearest match. This enables the system to determine team affiliations, which assists in tracking players and detecting fouls accurately.

3) Pose Estimation & Depth Sensing:
Pose Estimation Algorithm of YOLO is used to track players' skeletal movements by capturing 17 key joint points. This helps in understanding player positioning, movement patterns, and potential violations like traveling or illegal screens.

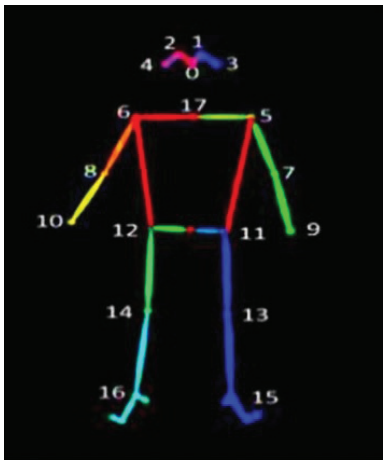

Fig. 2: Pose Estimation of 17 body joints

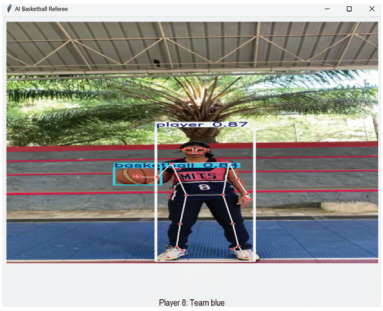

Fig. 3: Player Tracking Result

IV. Action Recognition based on Pose Estimation

Action recognition is conducted using deep learning models that analyze player movements over time:

1) Dribbling – Identified by following the vertical motion of the ball. If the ball goes down and then comes back up, it's a dribble.
2) Holding the Ball – When the ball stays within a constant distance of both wrists for over 0.85 second, it's assumed that the player is holding the ball.
3) Releasing the Ball – When the ball crosses the holding range, it is deemed released, restoring the holding state.
4) Step Count - It counts steps by tracking the movement of the ball handler's ankles using YOLOv8 pose detection. It compares the current and previous ankle positions and counts a step if the movement exceeds a set threshold. To prevent false counts, a short waiting period is used between steps.The step count resets when the player dribbles.

Fig. 4: Step Action Detection

Fig. 5: Hold Action Detection

V. Violation Detection

Violations in basketball occur when players break the rules, leading to a stoppage or turnover. Some common violations include traveling, double dribble, and time violations (8-second, 24-second, and 5-second rules), which help keep the game fair and fast-paced.

1) **8-Second Violation**
   The system monitors the position of the ball and applies a timer to verify whether the offensive team crosses half-court within 8 seconds. If they fail to do so, an offense is identified.
2) **24-Second Violation**
   The system tracks game time and shot attempts. When no shot is attempted within 24 seconds of possession, the system flags a violation.
3) **5-Second Violation**
   By tracking defenders' proximity, the system identifies when a closely guarded player holds the ball for over 5 seconds without passing, dribbling, or shooting.
4) **Double Dribble**
   If the player dribbles again after holding the ball, a double dribble violation is detected, triggering a red screen alert displaying "Double Dribble."
5) **Travel Violation**
   If the player takes 3 or more steps without dribbling, a travel violation is detected, and a warning is displayed.

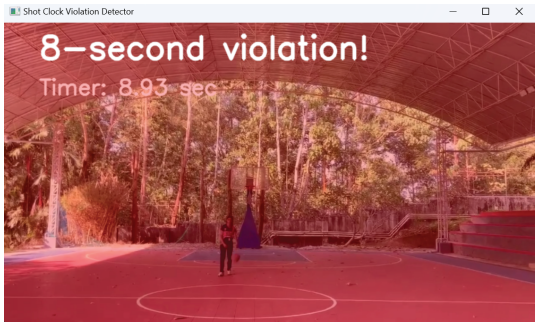

Fig. 6: 8-second Violation Detection

Fig. 7: 24-second Violation Detection

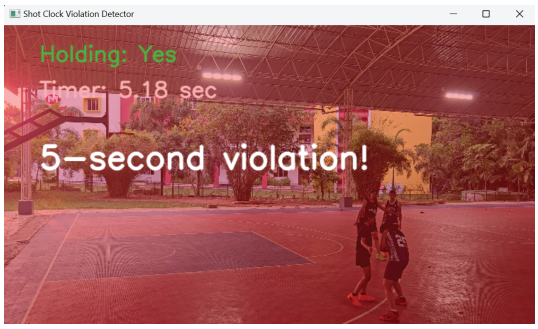

Fig. 8: 5-second Violation Detection

Fig. 9: Double Dribble Violation Detection

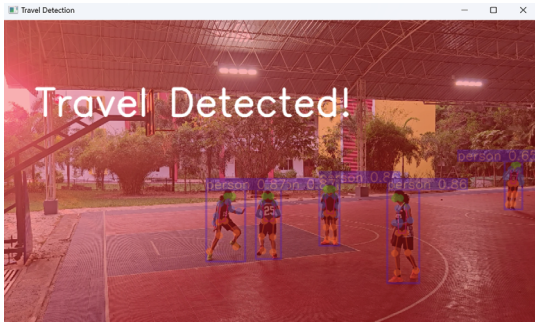

Fig. 10: Travelling Violation Detection

VI. Alert and Display

Our basketball referee assistant system is a web-based platform that helps referees, officials, and spectators by notifying game violations in real time. Powered by a Django backend API and a React frontend, it detects violations. The moment a violation is spotted, the system triggers an audible alarm and displays the violation type on the screen, making it easy for referees to make quick decisions.

VII. Results and Discussion

We have trained two YOLOv8 models to improve basketball officiation. The first model identifies the ball, rim, and players with 88.19% accuracy, and the second model identifies court features such as the full court, half court, and half-line with 64.24% accuracy. The models are trained for 50 epochs and form the basis of real-time rule violation detection to raise the accuracy of officiation.

Model (A) identifies elements like the rim, players, and ball with an overall accuracy of 88.2%. Model A is best at detecting basketball (98.2%), rim (99%) and the player (67.4%). High recall and precision indicate good detecting capacity.

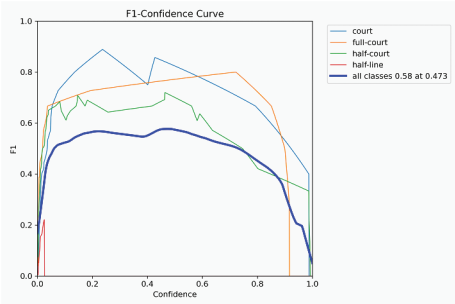

Fig. 11: Model(A) F1 Curve

Class	Images	Instances	P	R	Accuracy
All	257	420	0.81	0.897	0.882
Basketball	185	206	0.909	0.985	0.982
Player	58	101	0.603	0.706	0.674
Rim	107	113	0.919	0.999	0.99

TABLE I: Model (A) Performance Metrics

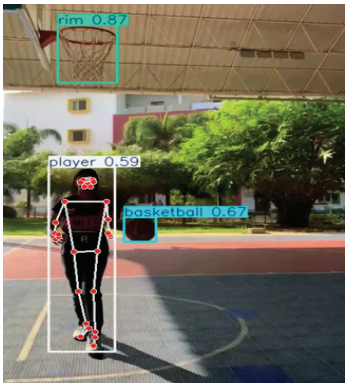

Fig. 12: Model(A) Test Result

Model (B) handles court-related detections, such as full court, half court, and half-line. It excels at high precision of near 1.0. The total accuracy is 64.2%.

Class	Images	Instances	P	R	Accuracy
All	10	33	0.951	0.495	0.642
Court	4	4	1.000	0.719	0.945
Full-Court	6	6	0.906	0.667	0.717
Half-Court	9	15	0.899	0.593	0.768
Half-Line	8	8	1.000	0.140	0.14

TABLE II: Model (B) Performance Metrics

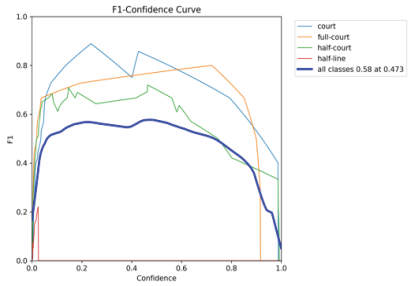

Fig. 13: Model(B) F1 Curve

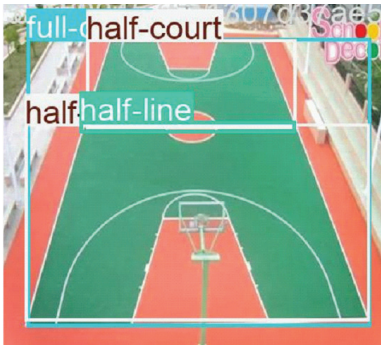

Fig. 14: Model(B) Test Result

VIII. Equations

1) Intersection over Union (IoU) is used to evaluate object detection models:

$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

2) The Euclidean distance formula is used for jersey color classification:

$$d = \sqrt{(R - R_c)^2 + (G - G_c)^2 + (B - B_c)^2}$$

3) To determine if a player is holding the ball, we calculate the Euclidean distance between the ball and both the left and right wrists.
The left wrist distance is calculated using the Euclidean distance formula:

$$\text{Left Distance} = \sqrt{(x_{\text{ball}} - x_{\text{left wrist}})^2 + (y_{\text{ball}} - y_{\text{left wrist}})^2}$$

where:

- $(x_{\text{ball}}, y_{\text{ball}})$ represents the coordinates of the ball center.
- $(x_{\text{left wrist}}, y_{\text{left wrist}})$ represents the coordinates of the left wrist.

Similarly, the right wrist distance is given by:

$$\text{Right Distance} = \sqrt{(x_{\text{ball}} - x_{\text{right wrist}})^2 + (y_{\text{ball}} - y_{\text{right wrist}})^2}$$

where:

- $(x_{\text{ball}}, y_{\text{ball}})$ represents the coordinates of the ball center.
- $(x_{\text{right wrist}}, y_{\text{right wrist}})$ represents the coordinates of the right wrist.

IX. Conclusion and Future Scope

The proposed AI-based basketball refereeing system in this paper enhances the fairness and accuracy of rule keeping using advanced computer vision algorithm like YOLOv8. Automated detection of fouls for traveling, double dribble, and shot clock violations reduces human errors and gives more consistent decisions. The extension of the system's functionality to automated score keeping and foul detection as well in future work will enable referees to make accurate and impartial decisions even more. Moreover, the incorporation of real-time feedback and multi-angle analysis can enhance the robustness of the system, and hence it can be an excellent tool for professional and amateur games. These enhancements will eventually result in an increased transparent and interactive experience for the players, referees, and spectators.

X. Acknowledgement

We sincerely thank our project guide, Mr Sumesh M S, Assistant Professor in the Department of Artificial Intelligence and Data Science, Muthoot Institute of Technology and Sci ence, for his timely guidance and valuable comments.

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OBJECT DETECTION & PAYLOAD FOR CUBESAT

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***Abstract*—The increasing amount of space debris poses significant risks to operational satellites and space missions. This study presents an object detection payload for CubeSat that uses LiDAR and spectroscopy to track and identify debris in orbit. The system enables real-time tracking and classification of space debris based on physical properties, enhancing space situational awareness. Spectroscopy analyzes debris material, while LiDAR measures distance, speed, and direction. The collected data is processed using Raspberry Pi 4 and displayed on a dedicated web platform for visualization and analysis. This research lays the groundwork for future CubeSat-based space debris tracking solutions**

Keywords—*CubeSat, LiDAR, Space Debris Detection, Spectroscopy, Object Tracking, Remote Sensing, Space Situational Awareness, Machine Learning.*

I. Introduction

The accumulation of space debris in Earth's orbit presents a critical threat to satellite operations, space stations, and future exploration missions. Fragments from defunct satellites, spent rocket stages, and mission-related debris contribute to an increasingly congested orbital environment, raising the likelihood of collisions. Conventional tracking methods, such as ground-based radar and optical telescopes, provide limited coverage and lack the ability to track smaller debris fragments effectively [1]. The need for an in-orbit monitoring solution has led to the development of compact CubeSat-based detection systems, which offer autonomous operation and enhanced real-time analysis. This research introduces a CubeSat payload that integrates LiDAR and spectroscopy for debris tracking and classification. LiDAR technology enables precise motion tracking by measuring an object's distance, velocity, and trajectory, while spectroscopy aids in material identification. The system's data is processed in real-time and visualized through a web-based platform, allowing for continuous monitoring. By leveraging advanced sensing and computation, the CubeSat provides a cost-effective, scalable, and efficient approach to space debris monitoring.

II. Literature Review

Numerous studies have explored space debris detection methods, with radar-based and optical tracking systems forming the foundation of current monitoring techniques. Radar offers high precision but requires substantial infrastructure, while optical telescopes provide detailed imagery but are affected by atmospheric distortions [2]. Recent advancements in LiDAR-based motion sensing have demonstrated high accuracy in terrestrial applications, including autonomous vehicle navigation [3]. Applying LiDAR to space debris tracking enables fine-grained motion estimation, complementing traditional approaches.

Spectroscopy has been widely adopted in remote sensing for material classification, with near-infrared reflectance spectroscopy (NIRS) proving effective in distinguishing different materials [5]. Research in satellite-based spectroscopy highlights its potential for identifying the composition of celestial bodies and artificial objects. Integrating spectroscopy into a CubeSat payload enhances classification accuracy, enabling distinction between metallic and non-metallic debris. Combining these technologies creates a robust, autonomous solution for real-time space debris analysis.

III. Methodology

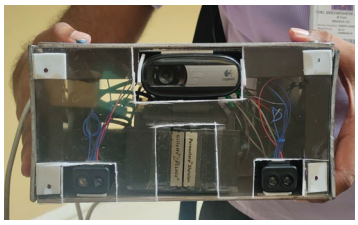

Fig 1 Cubesat Prototype

The CubeSat payload integrates multiple sensor technologies to achieve real-time space debris detection and classification. The system comprises three primary technologies: LiDAR for motion tracking, spectroscopy for material identification, and optical sensing for continuous

object tracking. The processed data is transmitted to a ground station via the CubeSat's communication module and displayed using a web-based platform.

A. LiDAR for Motion Tracking

LiDAR (Light Detection and Ranging) technology is used to measure the distance, speed, and trajectory of space debris [4]. The system consists of two TF Luna LiDAR sensors placed at opposite ends of the CubeSat, emitting laser pulses to detect objects, with the reflection time determining the distance. Since LiDAR is independent of ambient light, it is well-suited for space applications. The sensors are connected to an Arduino, which processes the data to extract distance (D), speed (S), and movement direction (dir, e.g., Left to Right: L2R or Right to Left: R2L). The Arduino transmits this processed data over a serial connection to a Raspberry Pi 4, which runs a Python script to continuously read the serial output and upload it to Supabase, a cloud database. The uploaded data is then retrieved and displayed on a web-based dashboard in the format.

`D:<int>; S:<int>; dir<L2R>.`

For example, `D:120; S:2; dir<L2R>`

represents a detected object at 120 cm distance, moving at 2 cm/s from left to right. The web interface, built using HTML, JavaScript, and Python (Flask or FastAPI), dynamically fetches and updates the latest LiDAR readings from Supabase in near real-time. The Python script running on the Raspberry Pi reads data from the Arduino, parses the values, and uploads them using an HTTP POST request to the Supabase API. This setup ensures real-time motion tracking of space debris, leveraging LiDAR, Arduino, Raspberry Pi 4, and Supabase to provide a fully integrated and cloud-connected monitoring system accessible via the web.

Fig 2 Tf Luna Lidar

B. Spectroscopy for Material Classification

Spectroscopy enables the classification of space debris based on its material composition by analyzing the light it reflects. The system employs a diffraction grating with 600 lines/mm, positioned at a 45-degree angle relative to the slits, to disperse the reflected light into its spectral components. An incandescent lamp serves as a controlled light source, ensuring a consistent spectral reference, while an ArduCam without an IR filter captures the reflected spectral data. The Raspberry Pi 4 processes this data, extracting the unique spectral signatures of materials such as copper, aluminum, and other metals to distinguish between different types of debris. The spectral analysis is conducted using PySpectrometer2, with the results visualized remotely through a VNC Viewer, enabling real-time monitoring and analysis. To enhance accuracy, calibration is performed using known reference spectra, ensuring precise material identification. This classification is crucial for determining the debris composition, aiding in the development of targeted removal or recycling strategies for space sustainability. The system's ability to operate autonomously in space makes it a valuable tool for debris tracking, contributing to the broader effort of mitigating space pollution and improving situational awareness in orbit

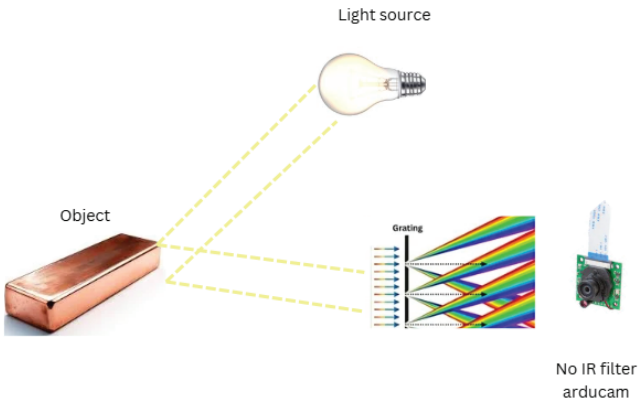

Fig 3 Setup of spectroscopy

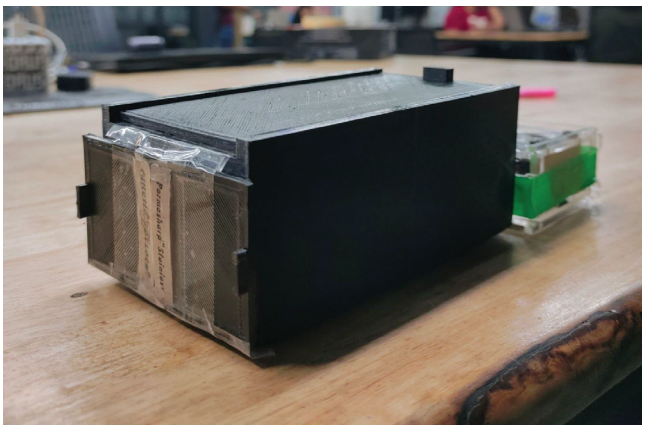

Fig 4 DIY Spectrometer

Fig 5 Slit of Spectrometer

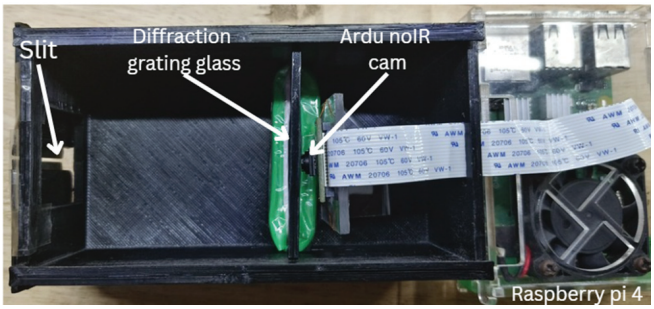

Fig 6 Inside View of Spectrometer

C. Optical Sensor for Object Tracking

An optical sensor enhances object tracking by capturing images of debris at regular intervals, providing visual data for analysis. In our experiment, we use the optical sensor to take images of the object and apply edge detection techniques to analyze its shape and contours. The Raspberry Pi 4 processes these images using computer vision algorithms, which detect and highlight the object's edges, helping to distinguish its structure from the background. This edge detection technique allows for a detailed assessment of the object's shape, which is crucial for classification and further analysis. The processed images and extracted edge data are stored for future examination and can be used to improve automated debris identification and tracking systems. This approach ensures a clear and precise visual representation of the debris, aiding in its characterization without relying on LiDAR data.

Fig 7 Webcam

D. Data Processing and Transmission

The Raspberry Pi 4 serves as the central processing unit, aggregating and analyzing data from LiDAR, spectroscopy, and optical sensors to provide a comprehensive assessment of detected debris. The collected data undergoes real-time processing, where LiDAR measures distance and speed, spectroscopy identifies material composition, and the optical sensor captures images with edge detection for shape analysis. Once processed, the data is transmitted to a ground station via a communication module, ensuring seamless data flow for monitoring and analysis. A Flask-based web application is used to visualize the collected data, allowing researchers to track and analyze debris in real-time. The web interface dynamically updates with the latest measurements, displaying key parameters such as distance, speed, material type, and object contours for efficient monitoring. The system is designed for autonomous operation, reducing manual intervention while maintaining high accuracy in classification and tracking, making it a reliable tool for space debris analysis and mitigation strategies.

IV. SYSTEM DESIGN

The CubeSat's architecture is designed with a modular framework, incorporating sensors, a processing unit, a power supply, and a communication module to enable efficient space debris monitoring. The LiDAR sensors detect object motion and provide trajectory analysis, while the spectrometer identifies material properties based on their unique spectral signatures. An Arduino Uno is dedicated to LiDAR data acquisition, handling raw sensor readings before transmitting them to the Raspberry Pi 4, which serves as the primary processing unit for data aggregation, analysis, and transmission. A LiPo battery ensures continuous power availability, supporting long-duration operation in orbit.

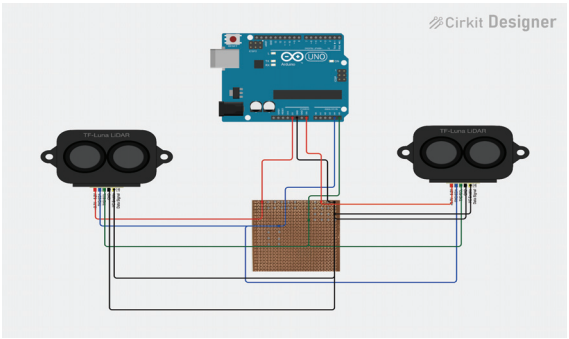

Fig 8 Lidar Setup

The software architecture integrates multiple layers to enable real-time processing and visualization. Embedded programming in the Arduino IDE is used for LiDAR control and data collection, while Python-based scripts on the Raspberry Pi 4 manage data processing, storage, and communication. The processed data is then transmitted to a Flask-based web application, which provides an interactive dashboard for researchers to track and analyze space debris in real-time. The system's real-time capabilities ensure seamless data flow between hardware components and the web interface, making it an effective and autonomous tool for orbital debris monitoring and classification.

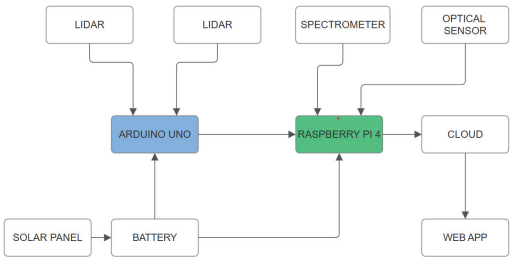

Fig 9 Block Diagram

V. EXPERIMENTAL SETUP & TESTING

To evaluate system performance, the CubeSat payload was tested under controlled conditions, simulating space debris detection. Experiments involved tracking objects with varying material compositions and motion characteristics to assess the accuracy of different sensors.

For motion tracking, the LiDAR sensors continuously measured object movement, providing real-time outputs in the format [6]

`D:<int>; S:<int>; dir<L2R>,`

where distance, speed, and direction were recorded exactly as detected. These values were displayed on a Flask-based web interface, ensuring real-time visualization of object motion without requiring comparison to reference values.

For material classification, spectroscopic analysis was conducted on metallic and non-metallic objects to identify material composition. The spectrometer analyzed the spectral signatures of different materials, successfully distinguishing between substances such as copper, aluminum, and other metals. The processed spectral data was displayed using PySpectrometer 2 via VNC Viewer, allowing researchers to observe material characteristics

The experimental results confirmed that the system effectively integrates LiDAR for motion tracking and spectroscopy for material identification, demonstrating its capability for real-time space debris detection and classification.

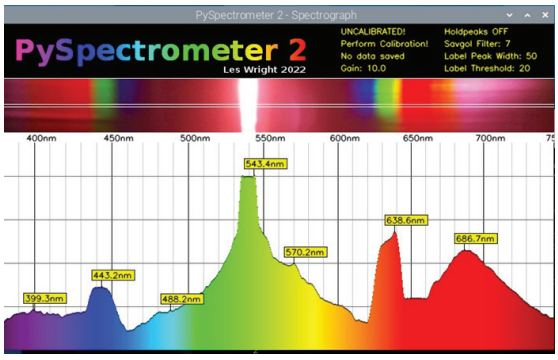

Fig 10 Incandescent Spectrum

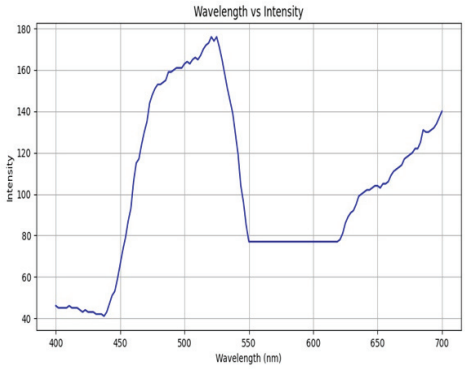

Fig 11 Incandescent Spectrum Graph

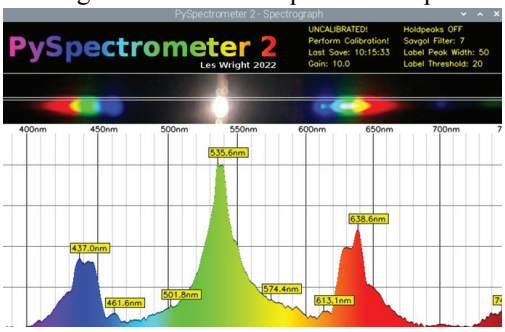

Fig 12 Led Spectrum

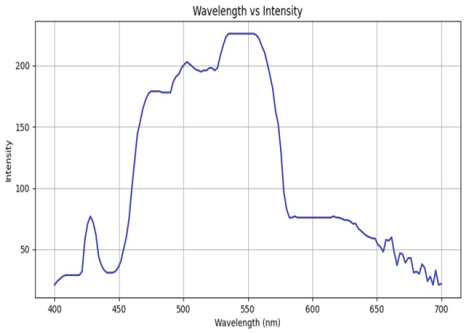

Fig 13 Led Spectrum Graph

VI. RESULTS & DISCUSSION

The CubeSat payload effectively demonstrated real-time space debris detection and classification through integrated LiDAR, spectroscopy, and optical sensing. The LiDAR system provided continuous tracking of object motion, displaying real-time distance, speed, and direction on the Flask-based web interface. The recorded LiDAR outputs accurately reflected object movement without requiring reference comparisons, confirming the system's ability to monitor dynamic space debris.

The spectroscopic analysis successfully differentiated metallic and non-metallic materials by analyzing their unique spectral signatures. The captured spectra, including the incandescent lamp's direct and reflected spectrum, validated the system's ability to detect light interactions with surfaces. These findings confirm the reliability of spectroscopy-based material classification for debris identification.

Additionally, the optical sensor enhanced debris analysis by capturing images and applying edge detection to assess object contours. This provided supplementary visual data for improved debris characterization. The Flask-based web interface enabled real-time data visualization, ensuring efficient monitoring of debris parameters.

Overall, the experimental results confirm that the integrated system is capable of accurate space debris tracking and classification, with real-time data processing and visualization, making it a valuable tool for orbital debris monitoring and analysis.

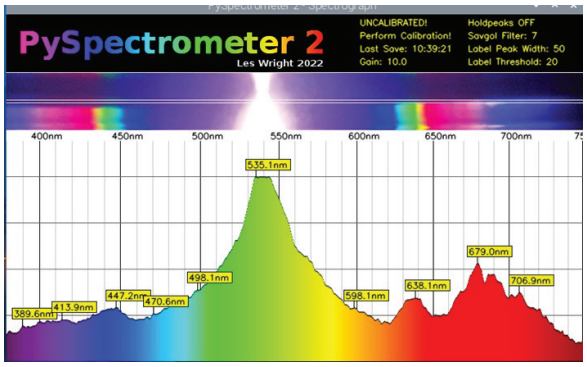

Fig 14 Transformer Reflected Incandescent Spectrum

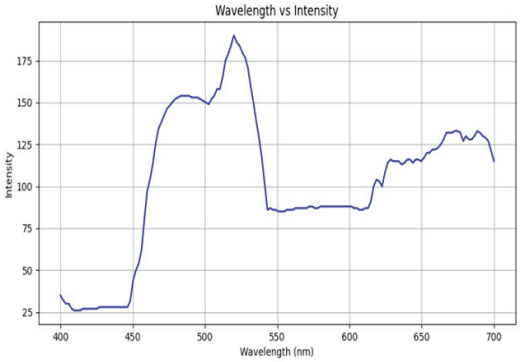

Fig 15 Transformer Reflected Incandescent Spectrum Graph

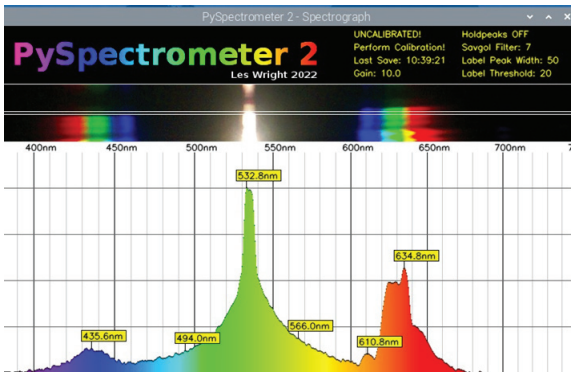

Fig 16 Transformer Reflected Led Spectrum

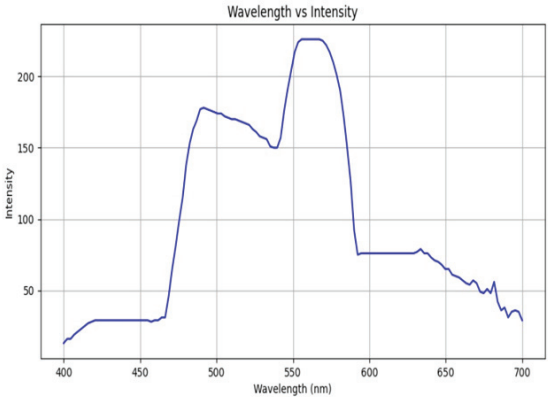

Fig 17 Transformer Reflected Led Spectrum Graph

VII. CONCLUSION AND FUTURE SCOPE

The CubeSat object detection payload successfully demonstrated autonomous space debris tracking and classification using an integrated system of LiDAR, spectroscopy, and optical sensing. The LiDAR system effectively tracked object motion, while the spectroscopic system captured and processed spectral data. The optical sensor further enhanced object characterization through edge detection. A Flask-based web interface provided real-time data visualization, ensuring seamless monitoring and analysis. Despite its success, challenges such as LiDAR range limitations, environmental factors, and data transmission constraints highlight areas for further development. These results confirm the system's potential as a reliable solution for space debris monitoring, with opportunities for refinement and real-world deployment.Future research will focus on integrating AI-based anomaly detection to enhance detection accuracy and automate material classification [7]. Expanding the system to networked CubeSat constellations will enable large-scale, coordinated space debris tracking, improving coverage and redundancy. Additionally, future exploration will investigate CubeSat-assisted debris mitigation strategies, such as robotic arms or electromagnetic tethering, to actively manage orbital debris. Advances in spectral analysis, including the incorporation of additional spectral bands, will further refine material identification capabilities. Beyond Earth's orbit, this technology could be adapted for planetary exploration missions, assisting in asteroid detection and interplanetary debris analysis. These advancements will significantly enhance space situational awareness and contribute to sustainable space operations.

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Enhancement of stability of BLDC motor by PID controller tuning

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***Abstract*— In the optimization of BLDC motor drive for high efficiency several challenges arise particularly when using harmonic minimization-based switching techniques. While optimizing harmonic reduction switching frequency will increase causing more frequent switching events. This can lead to greater switching losses which leads to reduction of system's efficiency. To mitigating these effects there are different type of method such advance control algorithms which can minimize harmonics more accurately. Employs techniques like Direct Torque Control (DTC) and optimized commutation sequence that minimize torque ripple. Tuning the PID controller is essential for achieving optimal performance, particularly when aiming to minimize harmonics and improve efficiency. Proper tuning helps that the motor responds accurately and smoothly with minimal torque ripple and stable operation. Tuning the PID controller is essential for stabilizing motor operation, reducing torque ripple, and ensuring smooth response. By combining these strategies a well-tuned efficient and robust BLDC motor drive can be achieved optimized for harmonic minimization and high performance across varying loads and environments.**

Keywords*— *BLDC, Optimization, PID, Torque ripple

I. Introduction

Permanent magnet trapezoidal brushless dc motors are efficient and have a faster response with high torque to volume ratio. Position sensing of these motor is essential to control the speed in a close loop and is required to trigger the gate switch in the universal gate switch. The demand for high-efficiency and precise control in brushless DC (BLDC) motors is rapidly increasing due to their extensive applications in electric vehicles, renewable energy systems, and industrial automation. BLDC motors are known for their high torque-to-weight ratio, fast response, and robust design, which make them highly desirable for applications where efficiency and performance are crucial. However, these motors can suffer from significant losses due to torque ripple, core losses, and switching losses in traditional drive systems. To address these issues, a novel control technique known as selective harmonic elimination pulse width modulation (SHE-PWM) has been proposed. This technique aims to minimize various types of losses by eliminating specific harmonic frequencies in the motor's phase current, thereby improving overall motor efficiency. The SHE-PWM method presents several operational advantages, particularly in reducing core and copper losses, and enabling a more stable torque output. However, implementing this method comes with challenges. The control strategy requires precise calculations and real-time adjustments in switching frequency to adapt to different load and speed conditions. Additionally, the need for high switching frequencies, while effective in harmonic reduction, may lead to increased inverter switching losses and could place a computational burden on the control hardware high-performance motor applications that require reliability, efficiency, and adaptability in dynamic environments. Lower-order harmonics, particularly the 3rd, 5th, and 7th harmonics, contribute significantly to torque ripple. By carefully choosing switching angles in the SHE-PWM control, these lower-order harmonics can be selectively suppressed in the motor's phase current. This helps in smoothing out the current waveform and directly reduces torque ripple. The harmonic elimination can be achieved by adjusting switching patterns based on the load and speed, which reduces the impact of unwanted harmonics on the torque output. The use of a lookup table with predefined switching settings can reduce torque ripple effectively by adapting to various load and speed conditions. However, incorporating an adaptive element in the lookup table allows the controller to adjust switching angles dynamically, rather than using static values. An adaptive lookup table enables real-time adjustments to the switching frequency and pattern based on instantaneous motor parameters. This helps to maintain low torque ripple even as motor conditions fluctuate.

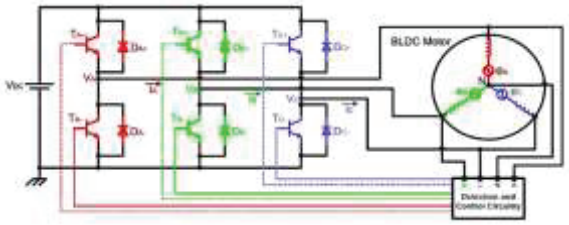

Fig 1. Basic Circuit Diagram for the BLDC Motor Control System.

II. SPEED CONTROL OF BLDC MOTOR BY PID CONTROLLER

The approach uses a close loop system with PID controller to maintain the motor at the desired speed. Logical gates and truth table (look up table) provide additional control logic, and PWM modulation and a universal bridge allow for precise power delivery to the motor. Fig 2 illustrates the block diagram representation of close loop system of BLDC motor with PID controller. To operate the system, a DC power supply is necessary, with its voltage level determined by the motor's speed (rpm) and capacity. A controller is also essential for this system, and a PID controller is employed to regulate the inverter's output voltage. A sensor plays a crucial role in a closed-loop control system for managing motor speed. Its main purpose is to transform the motor shaft's physical position and state into a corresponding electrical signal for the controller circuit. Generally, a BLDC motor requires an AC-like voltage waveform for operation, making an inverter circuit necessary to convert the DC supply voltage into an equivalent AC voltage to ensure proper functionality.

A. The working of the system

The system begins with a reference speed block that set a target speed. This reference speed is compared with the actual motor speed, and resulting error is sent to the PID controller. The PID controller process this error to adjust the duty cycle of the PWM signals that control the motor. The duty cycle signal feeds into a PWM generation block, which produce the appropriate gate signals to drive the switch in the universal gate. The universal gate converts DC supply into three phase voltage which powers the motor by switching current through the 3-motor phase (A, B, C) Fig 3 illustrates the circuit diagram representation of close loop system of BLDC motor with PID controller The motor block in the model represents the physical motor, which receives these three phase inputs and generates torque and rotational speed as outputs. The motor also provides the feedback signals, including phase current, rotational speed, and electromagnetic torque. These signals are monitored and fed back into the control system. The decoder block possibly using hall effect sensors or back EMF sensing, measures rotor position or speed and provides feedback to ensure accurate control of the motor. This system continuously adjusts the PWM signals to match the motor speed with the reference speed, ensuring precise control of the motor's operation.

The decoder uses a truth table to determine the appropriate switching sequences based on the rotor position or back EMF feedback. **Table I** displays the decoder sequences of the designed three-phase PID controller for the BLDC motor to turn in the clockwise direction. In BLDC or PMSM control, the truth table is essential for accurately controlling the phase current in sync with the rotor's position, which ensure efficient torque production and smooth rotation. In this motor there are three hall sensors, each sensors output can be either high (1) or low (0), providing a 3- bit code that corresponds to six unique rotor position within an electrical cycle. The decoder can estimate the rotor position from back EMF voltages if the sensors are not used. Table 1 illustrates the typical truth table for the three phase PMSM motor. As the rotor moves the hall sensors detect the rotor position and change their outputs accordingly. The decoder uses the truth table sues the truth table to translate these sensors output into the correct switching signals for the universal bridge. For every unique combination of sensor outputs, the truth table specifies which phase should energized, effectively controlling to the current flow through the motor to create rotational torque. The output of the truth table directly controls the gate signals sent to the bridge. These gate signals determine which switch in the inverter are activated, thereby controlling the current path in the motor windings. This current path aligns the magnetic fields of the stator with the rotor's magnetic field, resulting in continuous rotation.

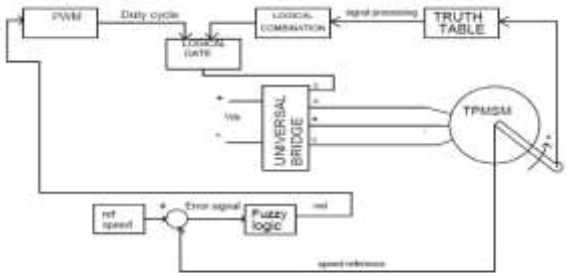

Fig 2. Basic Block Diagram for the BLDC Motor Close loop system

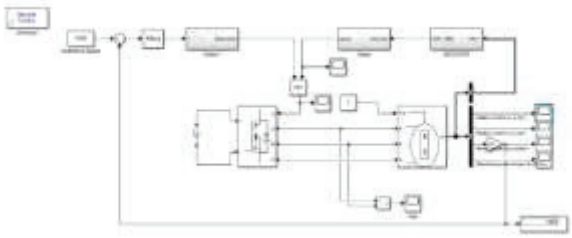

Fig 3 MATLAB Simulink of BLDC motor with PID controller

TABLE I. Look up table for Decoder

Table I	Truth table for decoder					
	ha	*hb*	*hc*	*Emf_a*	*Emb_b*	*Emf_c*
	0	0	0	0	0	0
	0	0	1	0	0	-1
	0	1	0	-1	-1	0
	0	1	1	-1	-1	1
	1	0	0	1	1	-1
	1	0	1	1	-1	0
	1	1	0	0	0	1
	1	1	1	0	0	0

III. RESULTS AND DISCUSSION

The effectiveness of the proposed PID controller for the brushless DC (BLDC) motor at 1500 rpm is depicted in Fig. 4. In this figure, the X-axis denotes time in seconds (sec), whereas the Y-axis represents the speed (rpm) of the BLDC motor under no-load conditions. The figure shows that the controller achieves a settling time of approximately 0.037 seconds, with minimal overshoot and undershoot. After this period, the motor maintains a steady speed of the predetermined 1500 RPM.

Fig 5 depicts the torque response behavior of the BLDC motor under no-load conditions. The X-axis represents time (seconds), while the Y-axis indicates the electromagnetic torque (Newton-meters, Nm). From the figure, it is evident that the electromagnetic torque stabilizes at a constant value after approximately **0.015 seconds**.

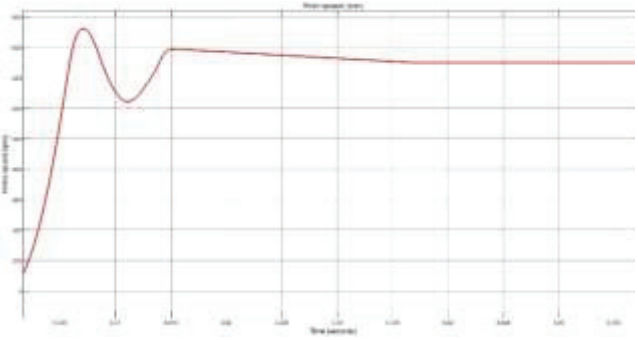

Fig 4 Rotor speed in no load condition of BLDC motor

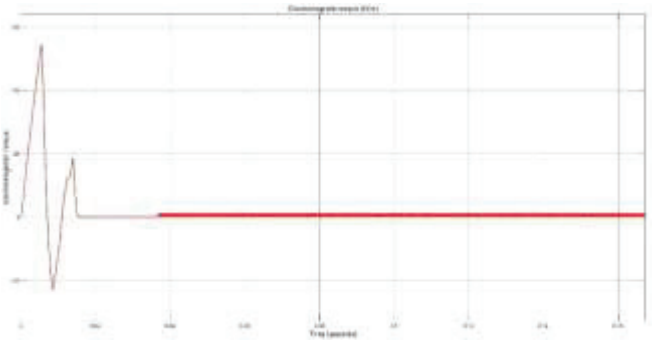

Fig 5 Electromagnetic torque in no load condition of BLDC motor

IV SPEED CONTROL OF BLDC MOTOR BY FUZZY LOGIC CONTROLLER

The fuzzy controller forms the core of the speed control mechanism. It receives two inputs: the actual motor speed (rpm) and the desired reference speed (N-rpm). Fig 6 shows the MATLAB Simulink of BLDC motor using fuzzy logic. The controller calculates the error between these two values and processes it using fuzzy logic to generate a control signal in the form of a duty cycle. This duty cycle determines the width of the pulses driving the inverter switches, effectively controlling the voltage applied to the motor and thereby adjusting its speed.

To ensure proper commutation of the motor phases, feedback from Hall sensors mounted on the motor is utilized. These sensors detect the rotor's position and send signals to a Hall Decoder, which processes them to produce the back-EMF signals (emf_ABC). These signals are crucial for determining the correct sequence of the inverter's switching operations. The AND logic gate combines these processed signals with control signals from the fuzzy controller, ensuring that the inverter gates operate in synchronization with the rotor position for efficient motor operation.

The system demonstrates a comprehensive approach to BLDC motor control by integrating feedback mechanisms, fuzzy logic, position sensors, and power electronics. The fuzzy controller adjusts the motor's speed by varying the duty cycle, while the hall sensor feedback ensures proper commutation for smooth operation. The simulation captures all critical parameters, offering insights into the motor's performance under various operating conditions, making it an effective tool for design and optimization.

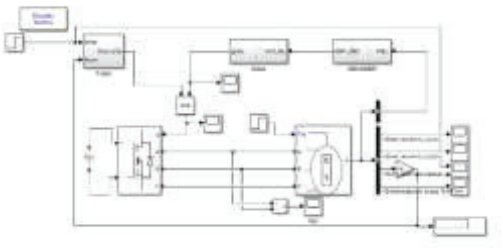

Fig 6 MATLAB Simulink of control of BLDC using fuzzy logic

V RESULTS AND DISCUSSION

Fig 7 shows the output performance of Fuzzy logic control. Hear the X-axis represents the time(s) and Y – axis represents the rotor speed (rpm). From the figure the red line represents the reference speed, while the blue line represents the actual rotor speed response. Initially, the rotor speed starts from zero and rapidly increases, exhibiting a significant overshoot beyond the reference value. This is followed by oscillations before gradually stabilizing at the desired speed. The transient response suggests that the system is slightly underdamped, as indicated by the overshoot and subsequent oscillations. However, the rotor speed eventually settles without any visible steady-state error, implying that the control system effectively regulates the speed. This behavior is characteristic of a feedback-controlled system, possibly using a PID controller or similar mechanism to achieve stability. The figure shows that the controller achieves a settling time of approximately 0.035 seconds

Fig 8 shows the electromagnetic torque the X- axis represents the time (s) and Y-axis represents the torque in N/m. From the figure it is seen that the oscillation has been settled out and come to a specific range and the torque peak-to – peak value has a small change as compared to Fig 5.

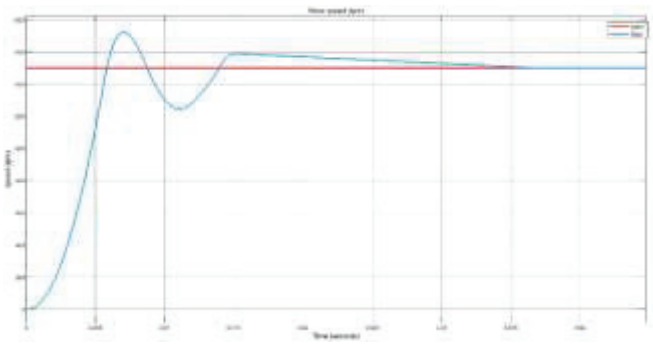

Fig 7 Rotor speed of BLDC motor after tuning of controller

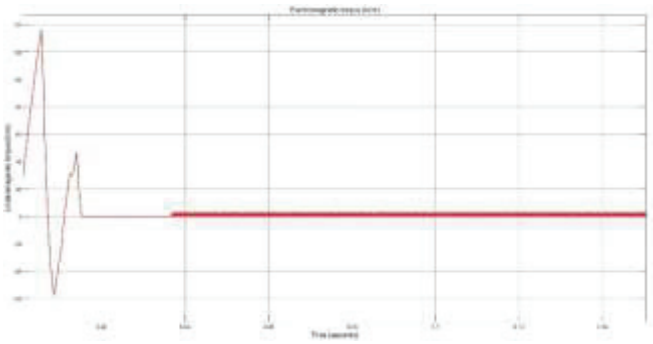

Fig 8 Electromagnetic torque after the tuning of controller

From the comparison it is understandable that the usage of Fuzzy logic is better for uncertain system and it is set back to previous state with in a short period of time.

V . Conclusion

A three phase BLDC motor has been designed and the stability of the system has been enhanced and optimized by using fuzzy logic control. The design has be validated with the help of MATLAB simulik.

Acknowledgment

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[5] Loss Minimization Control of Interior Permanent Magnet Synchronous Motors Considering Self-Saturation and Cross-Saturation Hamidreza Pairo†, Mohammad Khanzade**, and Abbas Shoulaie* †,*Dept. of Electrical Engineering, Iran University of Science and Technology, Tehran, Iran **Dept. of Information and Communication Technology, Comprehensive Imam Hosein University, Tehran, Iran

[6] Torque ripple suppression of brushless DC motor drives using an alternating two-phase and three-phase conduction mode *Zicheng Li1 , Qingyao Kong1, Shanmei Cheng2, Jiang Liu2*

Unlock the Secrets of Students Stress: A Multimodal Stress Analysis using Machine Learning Techniques

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***Abstract*—Various stressors such as academic work, social interactions, perceived parental expectations, exam-related pressure, and overwork often characterize a student's life. Research suggests that a degree of stress is required to catalyze academic performance, but excessive stress negatively affects student's general health. In particular, 70% of the students report that depression and anxiety are significant problems in their learning community. Stress is detrimental to our mental health, leading to poor academic performance, an increased risk of dropping out from studies, and problems in the overall well-being of students. To overcome this, we used a well-organized framework to quantify stress through a three-stage evaluation process. The first step involves a validated stress measurement tool called the Perceived Stress Scale (PSS), which is used to evaluate the level of stress in the student. After the PSS Questionnaire, background information such as student sleeping patterns, frequency of headaches, academic performance, study load, and participation in extracurricular activities to analyze stress levels using Random Forest (RF). The third step involves sentiment identification, where textual or audio data from students are classified as stressed or not stressed using Extreme Gradient Boosting (XGBoost). The combined results of these three steps produce a stress index report for each student with appropriate recommendations for managing stress. In this competitive academic environment, this system can be used as a tool for mentors to detect and help students to manage higher stress levels.**

***Index Terms*—Multimodal, Sentiment Classification, XGBoost, Random Forest**

I. Introduction

In today's academic environment, students are subject to a great amount of stress from studies, social pressures, and personal responsibilities. They must balance assignments, exams, and extracurricular activities, which are tense. While a small amount of stress keeps them going, excess stress over a period of time can harm their health and performance. It can cause issues like anxiety, depression, and even severe issues like suicidal tendencies. A study proposes that most of the students are under a significant amount of stress, which harms their physical as well as mental health. Alarmingly, even though student stress is a serious issue, there are no appropriate mechanisms available to identify and resolve it in a correct way.

To tackle this problem, our paper proposes a stress analysis system with multiple sources of information to collect an overall picture of student's stress levels. The system integrates various methods, such as Machine learning, Sentiment analysis, and Psychological tests, to identify student's stress patterns. The system is implemented in three primary phases. First, it evaluates their stress level using popular psychological scales, scientifically developed to measure stress. Second, it examines significant behavioral indicators such as sleep, study load, and academic performance to determine the degree to which these contribute to stress. Third, it processes the student's text or audio answers to identify their emotional

state. With the integration of all these methods, our model offers an accurate and overall picture of a student's stress level. This data proves to be beneficial both for students and mentors, who can detect stress at an early stage and implement appropriate measures to deal with it successfully. This research is developed to help institutions and mentors to recognize stress in students early and take the required steps to support them. Through the observation of how students participate in discussions, feedback, and emotions, our system can detect signs of stress. It then produces detailed stress reports for individual students and provides them with customized tips to manage stress better. The main goal of this system is to offer help before stress becomes a major concern. Instead of waiting for students to suffer, it helps to recognize problems early so that action can be taken promptly. This way, students receive the support they need to stay mentally fit and perform well academically. If the scenario is handled in the right way, students can focus better, stay motivated, and perform well in their studies without negatively affecting their mental well-being. Our strategy is developed to bring a balance between learning and emotional well-being so that students grow in a healthy and nurturing environment.

II. LITERATURE STUDY

Development of Stress Detection System Based on Heart Rate Using Artificial Neural Network focuses on detecting stress levels by analyzing heart rate variability (HRV).HRV refers to the changes in time intervals between heartbeats and is closely linked to emotional and physiological stress responses. Research shows that HRV helps measure autonomic nervous system activity, which plays a key role in how the body reacts to stress. This study uses Artificial Neural Networks (ANNs)to recognize complex patterns in heart rate data and predict stress levels. Unlike traditional methods, ANNs can detect subtle changes in heart rate, making them useful for continuous, non-invasive stress monitoring in mental health applications.However, the study has some limitations. The small sample size may not fully represent different stress responses, and factors like physical activity, medication, and environment are not considered, which could affect accuracy. Future research should focus on larger and more diverse datasets to improve the model's reliability and make it more effective for real-world stress detection.[1]

Tree-Based Multiclass Learning Model for Physiological Stress Detection from Students Community focuses on detecting stress in students using machine learning, as academic pressure makes early stress identification crucial. Traditional methods rely on self-reports, which may not always be reliable. To improve accuracy, this study applies tree-based models like Decision Tree, Random Forest, AdaBoost, and XGBoost to classify stress into low, moderate, and high levels. Random Forest reduces overfitting, and boosting techniques like XGBoost and AdaBoost enhance accuracy. The models were implemented in Python using Scikit-Learn, with data preprocessing handled by Pandas and NumPy, and visualized using Matplotlib and Seaborn. The approach allows real-time monitoring, making it useful for wearable technology and educational institutions to offer better mental health support.[2]

Mental Health Prediction Models Using Machine Learning in Higher Education Institutions applies machine learning to predict mental health issues like stress, anxiety, and depression among university students. Using data from the DASS-21 and WHOQOL surveys, it employs models like Decision Trees, SVM, Logistic Regression, and Multilayer Perceptron. SVM performed best for detecting depression (88.15% accuracy), while Decision Trees were most effective for stress (84.44%). The approach helps institutions monitor student well-being at scale, offering objective insights for early intervention. However, it relies on self-reported data and lacks real-time tracking, limiting personalization. Despite these challenges, machine learning provides a promising, data-driven method for mental health support in higher education.[3]

Automatic Detection of Twitter Users Who Express Chronic Stress Experiences via Supervised Machine Learning and Natural Language Processing uses NLP and machine learning to identify Twitter users experiencing chronic stress by analyzing stress-related tweets. Models like SVM, Random Forest, Naive Bayes, and BERT were trained on labeled tweets, with BERT achieving the highest accuracy (83.6%). NLP techniques such as sentiment analysis and word embeddings helped capture emotional tone and stress patterns. The approach is scalable and cost-effective, enabling real-time stress monitoring without clinical data. However, it has limitations, including reliance on self-reported tweets, language constraints, and privacy concerns. Despite these challenges, the study highlights Twitter's potential for large-scale mental health insights.[4]

A BERT Framework for Sentiment Analysis of Tweets explores the use of BERT for sentiment analysis of tweets, comparing its performance with traditional models like CNN, RNN, and BiLSTM. BERT outperforms these models, achieving 93% accuracy and a 95% F1-score by effectively understanding word relationships in tweets. The research highlights its potential for applications in marketing, public relations, and mental health. However, BERT struggles with classifying complex emotions like happiness and sadness, indicating the need for improved models. Despite its limitations, the study demonstrates BERT's effectiveness in sentiment analysis and suggests future advancements for a better emotional understanding in social media content.[5]

Ensemble BERT: A Student Social Network Text Sentiment Classification Model Based on Ensemble Learning and BERT Architecture introduces Ensemble BERT, a sentiment classification model that combines multiple BERT classifiers using ensemble learning and majority voting. It analyzes student interactions on China's Weibo platform to understand their emotions in digital spaces. The model improves accuracy and reduces individual classifier bias while maintaining a lower

computational cost than deeper BERT models. However, it requires 11.58% more training time and focuses only on a three-layer configuration. Despite these limitations, Ensemble BERT offers a reliable approach for sentiment analysis in educational settings, highlighting the importance of refining models for better student sentiment assessment.[6]

III. METHODOLOGY

To develop a multimodal stress detection system, several key steps were followed. First, the StressLevelDataset from Kaggle was utilized for stress level analysis, consisting of 20 stress-related features. Secondly, social media data from Twitter and Reddit were used for sentiment identification, containing stress-related text labeled as 1 for stressed and 0 for not stressed. Using Natural Language Processing the social media data is preprocessed to identify the relevant words that contribute to identifying the sentiment of the sentence, which are classified into the categories stressed or not stressed.

The Perceived Stress Scale (PSS) questionnaire, the Stress Level Analysis module, and the Sentiment Identification module each independently assess stress indicators and contribute to a comprehensive evaluation of a student's mental state. The system applies advanced machine learning algorithms, including Random Forest for stress level classification and Extreme Gradient Boosting (XGBoost) for sentiment identification. By combining these approaches, the system generates a holistic assessment of student stress and provides actionable insights for early intervention.

The proposed system consists of 5 modules that are shown in the system architecture in Fig:1.

The system includes:

- Preprocessing module
- PSS Questionnaire module
- Stress Level Analysis module
- Sentiment Identification module
- Report Generator module

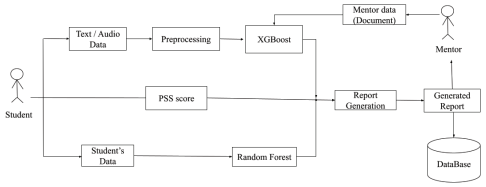

Fig. 1. Architecture Diagram

1)Preprocessing

Preprocessing is an essential step that prepares text data for analysis by cleaning and structuring it. This helps improve model accuracy and ensures better performance. • Noise Removal: Raw text data often contains unwanted elements such as mentions (@username), URLs, special characters, and redundant spaces. These are removed using regular expressions to ensure data consistency. Additionally, the text is converted to lowercase to avoid discrepancies caused by case differences.

• Tokenization: The text is divided into individual words (tokens) using the Natural Language Toolkit (NLTK)'s word tokenizer. This step facilitates further processing by enabling word-level analysis.

• Stopword Removal: Common words such as "the" and "is" are removed using the NLTK stopword list. However, negations (e.g., "not", "no") and intensifiers (e.g., "very") are retained to preserve sentiment context.

• Text Representation (TF-IDF Vectorization): The TfidfVectorizer from sklearn converts the 'Title' text into numerical vectors, capturing the importance of words while reducing the influence of common words. Padding is applied to ensure uniform sequence lengths, enhancing model compatibility..

• Handling Imbalanced Data: In cases where one sentiment category has significantly fewer samples than others, resampling techniques from Scikit-learn are employed to balance the dataset. This prevents bias in the model and improves generalization.

2)Perceived Stress Scale (PSS) Questionnaire

Fig 2 shows the Perceived Stress Scale (PSS) [7], which is a widely used psychological tool for measuring how individuals perceive and experience stress in their daily lives. It consists of 10 questions designed to assess how unpredictable, uncontrollable, and overwhelming life has felt over the past month. A typical question might be, "In the last month, how often have you felt nervous and stressed?" Participants respond using a 5-point scale, with options ranging from Never (0) to Very Often (4). This structured approach allows for a standardized assessment of perceived stress levels.

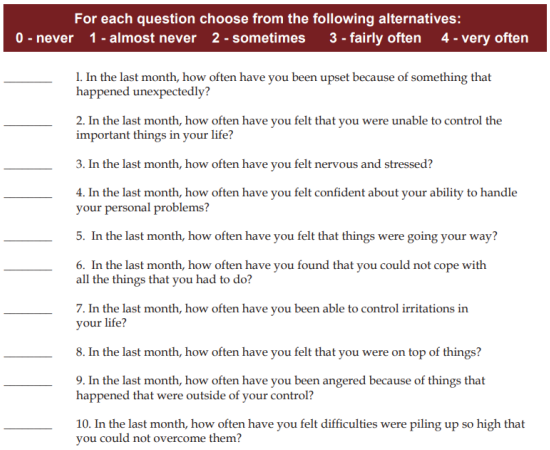

Fig. 2. Perceived Stress Scale

To improve accuracy, certain questions (specifically 4, 5, 7, and 8) use reverse scoring, meaning lower scores on these questions indicate higher stress levels. For instance,

if a respondent selects 0 (Never), it is converted to 4 (Very Often), and vice versa. Once all responses are scored, they are summed up to generate a total stress score, which falls within a range of 0 to 40. Based on this score, stress levels are categorized into three groups: low stress (0–13), moderate stress (14–26), and high stress (27–40). This classification helps in identifying individuals who may require intervention or stress management support. The PSS is a valuable tool in research and practical applications, particularly in understanding stress trends among students and guiding well-being initiatives.

3)Stress Level Analysis

The Student Stress Factors: A Comprehensive Analysis dataset is utilized to evaluate stress levels among students. It consists of 1,100 records and 20 features, covering various academic, psychological, and lifestyle factors, with no missing values, ensuring data integrity.

Feature-Based Self-Assessment on a 1-10 Scale, students provided self-assessed ratings on a scale of 1 to 10, where 1 indicates minimal impact and 10 signifies extreme severity. The dataset captures key stress-related features, including:

• Psychological Factors: Anxiety levels, emotional well-being, and mood stability.

• Academic Pressure: Study workload, assignment deadlines, and exam stress.

• Lifestyle and Health Indicators: Sleep quality, social interactions, physical activity, headaches, and fatigue.

A Random Forest classifier with 100 decision trees is trained to analyze these responses, identifying complex interactions between stress-related variables. The model predicts stress level, categorizing students into low, moderate, and high-stress groups based on their responses. By integrating self-assessment responses with deep learning techniques, this system enables a data-driven approach to stress detection, facilitating early intervention and improved student well-being.

4)Sentiment Identification

The sentiment identification module is a critical component of the stress detection system, responsible for analyzing text inputs to determine emotional tone and identify signs of stress. This module plays a key role in the early detection of psychological distress by processing textual data and classifying it as either ”stressed” or ”not stressed.”

Once the text data is preprocessed, the system employs a combination of TF-IDF (Term Frequency-Inverse Document Frequency) vectorization and the Extreme Gradient Boosting (XGBoost) algorithm to extract meaningful features and perform sentiment classification. The text is first transformed into numerical representations using TF-IDF, which highlights the importance of words while reducing the influence of common terms. The XGBoost model then analyzes these representations to identify stress-related patterns efficiently.

To maintain the accuracy and consistency of the sentiment classification, the system incorporates robust validation mechanisms. This involves cross-referencing predictions with known sentiment labels and analyzing model performance through standardized evaluation metrics, ensuring the reliability of the sentiment identification process. Additionally, confusion matrices and classification reports are generated during training and validation to track and improve model performance over time.

5)Report Generator

The Report Generator plays a crucial role in combining different assessments to determine a student’s overall stress level. It gathers data from three sources: the Perceived Stress Scale (PSS) Questionnaire, which measures stress levels as Low, Medium, or High; Student Performance Analysis, which categorizes academic performance into Low, Medium, or High; and Sentiment Analysis, which evaluates student’s text-based responses to identify signs of stress (Yes or No). Once all these assessments are collected, the system determines the final stress level by following a majority ranking approach. If most indicators suggest High stress, the final classification is High Stress. If the indicators are mixed, the system assigns Moderate Stress, and if most indicators suggest Low stress, the final classification is Low Stress.Beyond just assigning a stress level, the Report Generator also provides recommendations tailored to each student’s result.By offering personalized insights and actionable recommendations, the Report Generator helps educators and students take proactive steps toward stress management, ensuring better mental well-being and academic success.

IV. CHALLENGES FACED

Developing an AI-driven stress level prediction system involves multiple challenges, including data variability, model interpretability, and real-world application constraints.

- **Handling Diverse Data Inputs:** Stress levels are influenced by various physiological and behavioral factors, making it difficult to ensure the model generalizes well across different individuals and environments.
- **Feature Selection and Processing:** Identifying the most relevant features for stress prediction is complex, as certain indicators may vary significantly based on personal habits, external conditions, and subjective experiences.
- **Model Accuracy and Bias:** Achieving high accuracy while minimizing biases in predictions is challenging, as stress perception differs among individuals, requiring extensive and balanced training data.
- **Real-time Prediction Constraints:** Implementing a system that provides quick yet reliable stress assessments in real-time requires optimizing computational efficiency without compromising prediction quality.
- **User Interpretability and Trust:** Ensuring that users understand and trust the AI’s stress level predictions is crucial, as unclear or misleading results could lead to unnecessary concern or neglect of real stress indicators.

V. RESULTS AND DISCUSSION

The stress level module applies machine learning algorithms for classifying persons into Low, Medium, and High stress levels based on numerous input features. The system learns from a Random Forest Classifier ensuring strong performance with high accuracy.

The model was tested against 330 test cases, where 297 were correctly classified, hence its robust predictive power in stress assessment. The reliability of the system in stress prediction makes it an important tool in mental health analysis, delivering accurate information for stress management and intervention.

TABLE I
PERFORMANCE OF STRESS LEVEL CLASSIFICATION

Class	*Precision*	*Recall*	*f1-Score*	*support*
0	0.86	0.89	0.88	113
1	0.92	0.92	0.92	107
2	0.92	0.88	0.90	110
accuracy			0.90	330

Table 1 presents the performance metrics of the stress level classification model, achieving an overall accuracy of 90%, demonstrating its effectiveness in distinguishing different stress levels. The model classifies stress into three categories: Class 0 (Low Stress), Class 1 (Moderate Stress), and Class 2 (High Stress). The classification report highlights robust performance, with F1-scores of 0.88, 0.92, and 0.90 for the low, moderate, and high-stress classes, respectively, ensuring a balance between precision and recall. The precision values of 0.86, 0.92, and 0.92 across the three classes demonstrate the model's reliability in minimizing false positives, while the recall values of 0.89, 0.92, and 0.88 confirm its ability to correctly identify stress levels. The results validate the system's capability in accurate stress assessment, making it a valuable tool for mental health monitoring and intervention.

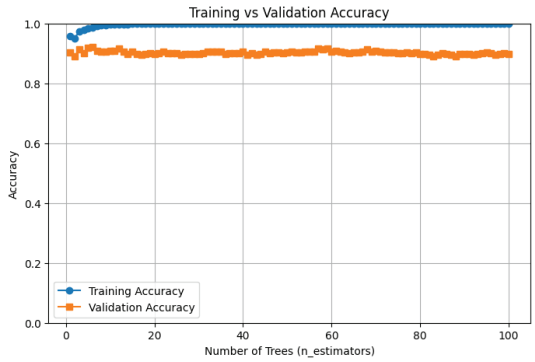

Fig. 3. Training vs Validation Accuracy of the Model

Fig:3 showcases the effectiveness of the Random Forest Classifier in achieving high accuracy with increasing numbers of trees (n_estimators). The training accuracy (blue curve) rapidly converges to 1.0, demonstrating the model's strong learning capability. The validation accuracy (orange curve) remains consistently high, stabilizing around 85% to 88%, indicating robust generalization to unseen data. This stability suggests that the model achieves an optimal balance between complexity and performance without unnecessary computational overhead. The results highlight the efficiency of the classifier in maintaining reliable accuracy, making it well-suited for real-world applications where both precision and generalization are crucial.

The Sentiment Identification module analyzes text inputs to detect emotional stress patterns from the social media dataset which consists of 16512 data, which is used for training the model. It uses TF-IDF vectorization to convert textual data into numerical representations. This module processes real-world student inputs, including textual reflections, to determine whether a given text expresses "stressed" or "not stressed."

TABLE II
COMPARISON PERFORMANCE OF BI-LSTM AND XGBOOST

Metric	*Class*	*Bi-LSTM Model*	*XGBoost Model*
Accuracy		0.85	0.84
Precision	0	0.86	0.87
Recall	0	0.85	0.79
Precision	1	0.84	0.82
Recall	1	0.86	0.89

Table 2 provides the comparison performance of Bi-LSTM and XGBoost algorithms, the model classifies stress into two categories: Class 0(not stressed) and Class 1(stressed). The Bi-LSTM model achieved an accuracy of 0.85% and the XGBoost model achieved an accuracy of 0.8428%. However, Bi-LSTM struggled with negations, misclassifying sentences like "I am not stressed" as stressed, while XGBoost handled such cases better due to its decision-tree-based learning. Bi-LSTM provides better accuracy and balance, while XGBoost is faster, more memory-efficient, and better at handling contextual cues like negations, therefore, XGBoost was selected for sentiment Identification.

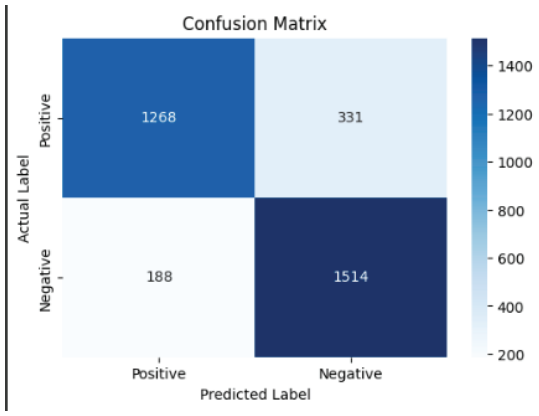

Fig. 4. Confusion Matrix of Sentiment Identification

Fig:4 is the confusion matrix for the model, it was observed that the model produced minimal errors, ensuring reliable sentiment detection.

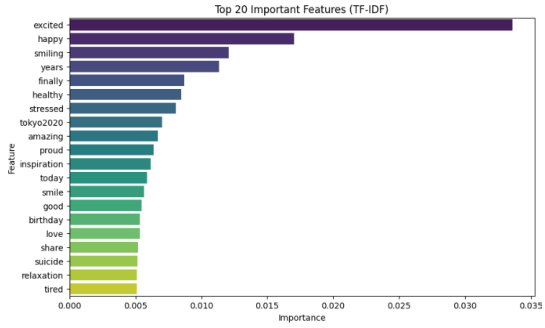

Fig. 5. Top 20 Important Features

Fig:5 gives the top 20 important terms revealed by the feature importance in identifying stress-related sentiments, enhancing the interpretability of the model. A random sample of 10 correct predictions was also extracted from the test dataset, further validating the model's performance across various textual inputs. This module provides a crucial emotional dimension to the system by detecting early signs of psychological distress through language patterns.

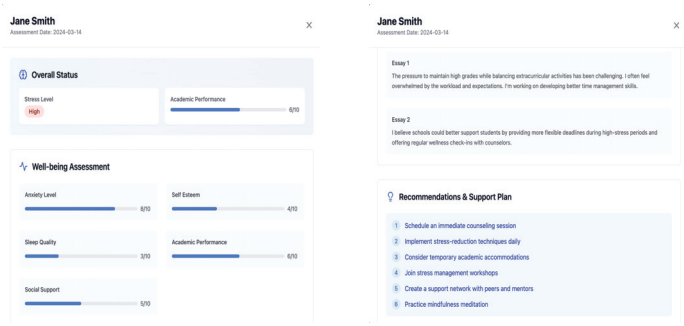

Fig. 6. Sample of Generated Report

Fig:6 shows the sample outputs by integrating all three modules, the system generates a comprehensive stress index report for each student. This report consolidates psychological assessments from the PSS questionnaire, behavioral insights from the Stress Level Analysis module, and emotional indicators from the Sentiment Identification module to deliver a holistic understanding of stress levels.

VI. CONCLUSION AND FUTURE SCOPE

The proposed multi-model framework provides a detailed approach to understanding student stress by combining two types of data: qualitative insights from students' text entries and quantitative scores from the Perceived Stress Scale (PSS) questionnaire. This combination offers a complete view of students' stress levels, helping mentors identify those who might need extra support. By gathering both personal reflections and measurable stress indicators, the system gives institutions a practical tool for supporting student mental health in a well-rounded way.

In the future, the system could be enhanced by providing even more Real-Time interventions by adding proctored assessments where Real-Time emotions of the student can be detected while attending the assessments for sentiment identification. Mentors could add specific prompts in text entries to guide students in expressing their stress sources more effectively. Tracking stress levels over time could help identify long-term patterns, enabling early intervention. Additionally, future updates could introduce admin access for institution counselors, allowing them to view and analyze student reports for better guidance and mental health support. This enhancement would enable counselors to monitor trends, identify at-risk students, and implement proactive interventions to improve overall student well-being.

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AI-Powered Service Provider Identification and Assessment Framework Using Context-Aware Language Processing

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***Abstract*—This investigation presents the creation of an innovative AI-enhanced service matching framework utilizing advanced language processing technologies to assist individuals in identifying nearby service experts for residential requirements, including electrical maintenance and mechanical assistance. The ecosystem employs computational linguistics to precisely comprehend user queries, delivering a two-fold response mechanism. When addressing minor challenges, the framework autonomously explores digital resources to suggest appropriate resolutions, enhanced with specially curated instructional video content. For more intricate service requirements, the ecosystem evaluates a dedicated repository of service experts. These providers undergo assessment through a specially adapted Bidirectional Encoder Representations from Transformers (BERT) architecture, which executes opinion mining on enhanced information—converting commercial product assessments into service quality indicators—while incorporating supplementary metrics such as professional validations and practical expertise. The technical infrastructure combines FastAPI for backend operations with React for user interaction components, ensuring seamless responsiveness and intuitive navigation. Quantitative assessments indicate this comprehensive methodology significantly enhances both operational effectiveness and recommendation accuracy for local service connections compared to traditional approaches.**

***Keywords*—Advanced language processing, service expert identification, opinion evaluation, BERT implementation, computational linguistics, server frameworks, interface technologies, information enhancement strategies.**

I. Introduction

In contemporary digital ecosystems, establishing efficient connections between consumers and neighborhood service specialists for residential requirements such as electrical maintenance and mechanical assistance remains a considerable challenge. Conventional service directories frequently lack individualization and fail to provide intuitive interaction models. To address these limitations, we have engineered an innovative service discovery platform enhanced by sophisticated language processing technologies that operates as an intelligent digital assistant, streamlining the identification and engagement of local service professionals.

Our framework harnesses advanced computational linguistics capabilities to interpret user inquiries expressed in conversational language. When addressing minor challenges, the system independently examines digital resources to suggest appropriate resolutions, complemented by carefully selected instructional video demonstrations. For more substantial service requirements, the platform evaluates a specialized repository of neighborhood service providers. To ensure recommendation quality and relevance, we implement a customized Bidirectional Encoder Representations from Transformers (BERT) architecture for opinion assessment. This model analyzes service excellence by examining enhanced datasets that transform commercial product evaluations into service quality indicators while incorporating additional parameters such as professional credentials and practical experience.

The framework's architecture integrates FastAPI for backend operations and React for user interface elements, ensuring responsive and intuitive interaction. By combining sophisticated language processing methodologies with user-centered design principles, our platform aims to revolutionize how individuals connect with neighborhood service providers, offering personalized, efficient, and dependable solutions to their residential requirements.

II. Literature Survey

Recent innovations in digital service matchmaking and textual evaluation techniques have profoundly influenced the evolution of intelligent service-recommendation ecosystems. One investigation introduces a language model-driven approach for

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position recommendation, addressing constraints in candidate profile quality by leveraging generative competitive networks to enhance profile representations. This methodology highlights the capacity of advanced language models to improve service suggestions by mitigating issues including fabricated information and limited user engagements. Similarly, alternative research discusses the progression of digital service directories, emphasizing the advantages of location-aware matching to enhance accessibility and operational efficiency for both service seekers and providers.

Another essential component of this investigation involves textual sentiment evaluation using sophisticated language processing technologies. Studies provide comprehensive overviews of opinion mining methodologies, demonstrating how architectures including BERT, GPT, and XLNet considerably enhance sentiment classification precision. The challenges of domain adaptation and inherent biases in language models are emphasized, alongside their effectiveness in extracting subjective insights from textual information. These perspectives are particularly relevant to our project, where opinion mining plays a crucial role in ranking neighborhood service providers based on consumer-generated feedback.

Our methodology integrates these advancements by implementing a customized BERT architecture to analyze service evaluations, transforming product-oriented sentiments into service quality indicators. Additionally, our framework utilizes a conversational interface to enhance user engagement, aligning with the recommendation-driven methodologies discussed in previous investigations. By combining language model-based opinion mining with a location-aware service discovery framework, our platform offers an innovative solution for optimizing service provider identification and assessment.

III. Methodology

The proposed framework represents an intelligent service discovery and neighborhood provider identification platform powered by sophisticated language processing technology. The ecosystem integrates a conversational AI interface to assist consumers in discovering relevant service specialists for residential tasks including electrical maintenance, mechanical assistance, and general household upkeep. The framework employs a dual-response mechanism: (i) delivering direct solutions through digital resource examination and instructional content for minor issues, and (ii) assessing and recommending service providers based on a customized opinion mining architecture. The assessment model implements a BERT-based framework trained on enhanced evaluation data to extract insights from consumer feedback, ensuring high-quality service recommendations.

A. Information Collection and Preparation

The dataset for training the opinion mining architecture comprises a combination of extracted service evaluations from various digital platforms, including e-commerce portals and service-based applications. To enhance model adaptability, the dataset incorporates evaluations transformed from product assessments into service-specific feedback, ensuring applicability to neighborhood service providers. Additionally, information sourced from platforms like Uber and comparable service aggregators were included to incorporate real-world service performance indicators.

The dataset underwent comprehensive preprocessing, including textual standardization, redundant element removal, word base extraction, and sentiment orientation annotation. Enhancement methodologies, such as equivalent term substitution and reverse translation, were applied to address information sparsity and improve generalization. The dataset was organized into an 80:10:10 distribution for development, validation, and assessment to ensure optimal performance during model evaluation.

B. Computational Framework

The core of the system's assessment mechanism is a customized BERT-based opinion mining architecture. BERT's bidirectional encoding capabilities enable the model to identify nuanced sentiment patterns within consumer-generated evaluations. The framework consists of a pre-trained BERT encoder, followed by a classification component comprising dense layers with dropout regularization to prevent overfitting. The model processes textual evaluations by extracting contextual embeddings, which are subsequently analyzed through a fully connected network to generate sentiment indicators. These indicators, combined with other assessment factors such as professional validations, practical experience, and consumer engagement metrics, contribute to the final ranking of service providers.

C. Interactive AI Ecosystem

The platform operates as a chatbot-driven ecosystem where consumers interact with an AI assistant to express their service-related inquiries. The language processing technology, integrated with FastAPI, analyzes natural language inputs to classify user intent and determine the appropriate response strategy.

Query Interpretation: The language model identifies whether the user inquiry relates to a minor issue resolvable via digital resource examination or requires assistance from a neighborhood service provider.

Resolution Identification: If the challenge is minor, the ecosystem retrieves relevant solutions, including web-based troubleshooting guides and selected instructional video recommendations.

Service Provider Identification: If the issue requires professional intervention, the system examines the service provider repository, identifying candidates ranked by opinion analysis indicators and professional credentials.

D. Model Development

The BERT architecture was customized using a supervised learning methodology on the preprocessed dataset. Development employed a cross-entropy loss function, and the Adam

optimizer was implemented with an adaptive learning rate scheduler. A batch size of 32 and a maximum sequence length of 256 tokens were selected to optimize training efficiency.
The model underwent evaluation using standard classification metrics including accuracy, F1-score, and AUC-ROC. Hyperparameter optimization was conducted using grid search to identify the optimal learning rate, dropout rate, and batch size.

E. Opinion-Based Assessment Framework

Each service provider in the ecosystem receives a sentiment indicator derived from consumer evaluations. The opinion analysis model classifies reviews into positive, neutral, and negative categories. A weighted aggregation function is applied, considering evaluation recency, provider response frequencies, and additional attributes such as professional validations and practical experience.
Sentiment Indicator Calculation:

$$S = \alpha P + \beta N + \gamma C$$

where P represents positive sentiment weight, N represents neutral sentiment weight, and C accounts for provider credibility metrics.
Assessment Methodology: Service providers undergo dynamic ranking based on computed sentiment indicators and additional filtering criteria, ensuring optimal recommendations for consumers.

F. Framework Output and Application

Upon query resolution, the ecosystem presents consumers with one of the following outputs:
Independent Solution: If the issue is minor, consumers receive comprehensive troubleshooting instructions alongside relevant instructional demonstrations.
Ranked Service Provider Catalog: If external intervention is necessary, consumers are presented with an assessed list of neighborhood service providers, facilitating informed decision-making.
Automated Scheduling Functionality: The platform features an integrated reservation system, enabling consumers to arrange appointments directly through the conversational interface.
By combining advanced computational linguistics methodologies with an AI-enhanced recommendation system, the proposed platform improves accessibility, reliability, and efficiency in discovering and engaging neighborhood service providers.

IV. Implementation and Results

A. Implementation

The proposed AI-enhanced service directory integrates a **customized BERT-based opinion analysis architecture** for assessing neighborhood service providers. The ecosystem functions through a **conversational interface**, allowing consumers to describe their service requirements in natural language. The AI component processes these inquiries, **determines user intent**, and establishes whether an issue can be resolved independently or if professional intervention is necessary.
The ecosystem operates in **two fundamental stages**: 1. If independent resolution is feasible, the platform identifies and presents **relevant instructional materials** such as text-based troubleshooting guides and selected video tutorials. 2. If professional service is required, the ecosystem implements an **opinion analysis architecture** to assess and recommend service providers based on multiple parameters including **historical consumer evaluations, professional validations, practical experience, and user engagement metrics**.
The **backend infrastructure** is developed using **FastAPI**, a high-performance, asynchronous web framework optimized for real-time interactions. The **user interface** is implemented using **React**, ensuring an intuitive and consumer-friendly experience. The ecosystem also incorporates an **automated reservation module**, enabling consumers to directly schedule appointments with neighborhood service providers.

B. Performance Evaluation

The performance evaluation of the models in the figure highlights significant differences in their ability to handle sentiment analysis tasks, based on metrics such as Accu racy, Precision, Recall, and F1 Score.

Table I: Performance Metrics of LLMs for Sentiment Analysis

Model	Accuracy	Precision	Recall	F1-Score
BERT	88%	86%	87%	87%
XLNet	87%	85%	86%	86%
RoBERTa	91%	89%	90%	90%
T5	89%	87%	88%	88%

BERT emerged as the top-performing model, achieving 94transformer-based architecture enables it to understand context effectively, making it highly accurate for nuanced sentiment analysis. LSTM followed, with 88-90Score of 88data, though it falls short of BERT due to its limitations in capturing long-range dependencies.

FastText demonstrated a strong performance with 85 across all metrics, providing a good trade-off between computational efficiency and accuracy. Its embedding-based approach works well for general sentiment tasks but lacks the advanced contextual understanding of BERT and LSTM. VADER and TextBlob, as lexicon-based models, showed moderate re sults, with VADER achieving 70-75slightly lower at 65-70rules and dictionaries, making them less effective for complex or domain-specific data.
The performance trends are visually depicted in Fig. 2, providing an **intuitive comparison of model accuracy, precision, recall, and F1-score**.

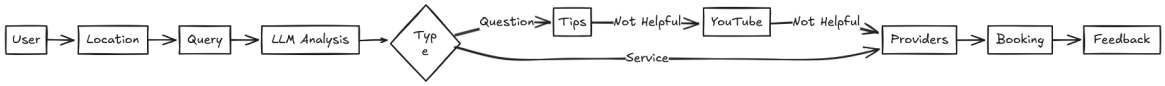

Fig. 1: Block Diagram

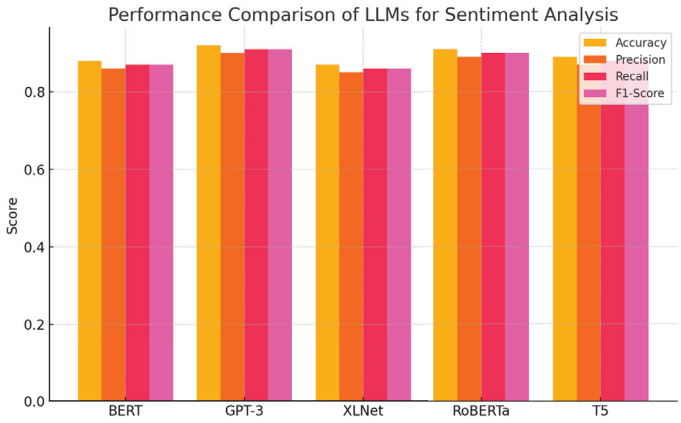

Fig. 2: Performance Comparison of LLMs for Sentiment Analysis

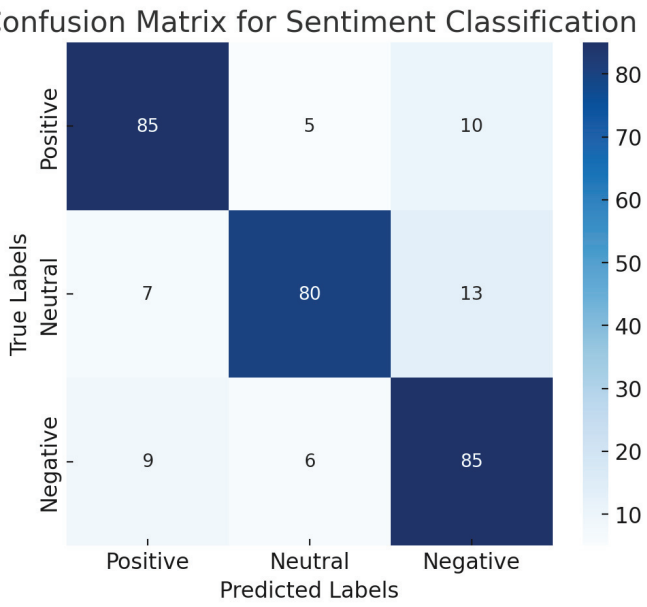

Fig. 3: Confusion Matrix for Sentiment Classification

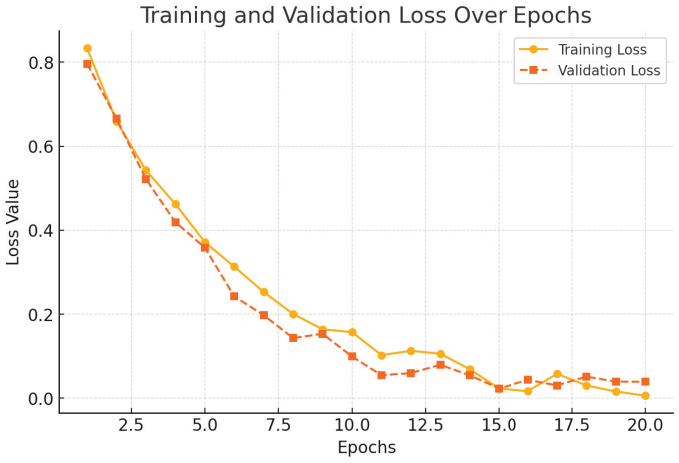

Fig. 4: Training and Validation Loss Over Epochs

C. Confusion Matrix Analysis

A **confusion matrix** provides deeper insights into the **classification effectiveness** of the opinion analysis architecture. Fig. 3 illustrates how effectively the **customized BERT model** performed across three sentiment categories: **Positive, Neutral, and Negative**.

The architecture correctly identified **85% of positive sentiments, 80% of neutral sentiments, and 85% of negative sentiments**. The **misclassifications** occurred primarily between **Neutral and adjacent sentiment categories**, highlighting challenges in distinguishing **moderately positive or neutral** consumer feedback.

D. Training Loss Analysis

To evaluate the learning behavior of our architecture, we monitored **training and validation loss** values across multiple epochs. The graph in Fig. 4 illustrates the gradual **reduction in loss values**, indicating successful model optimization.

Initially, the architecture exhibited **elevated loss values**, reflecting challenges in accurately classifying textual sentiments. As development progressed, the loss steadily declined, **stabilizing after approximately 15 epochs**, confirming that the architecture had effectively learned from the dataset.

Notably, the **minimal difference between training and validation loss** suggests that the architecture generalizes effectively to unfamiliar data, ensuring robust real-world performance.

E. Findings and Discussion

The experimental results confirm the effectiveness of **language model-based sentiment-driven assessment** in a service discovery application. The following key insights emerged from our investigation:

- **RoBERTa outperforms alternative architectures:** Its superior accuracy (91%) and balanced precision-recall performance establish it as the optimal candidate for **high-quality sentiment classification**.
- **BERT maintains significant reliability:** Given its **balanced equilibrium** between efficiency and performance, BERT represents an ideal solution for **real-time appli-**

cations with computational limitations.

- **Customization substantially enhances architectural accuracy:** Sentiment classification benefits considerably from **domain-specific information training**, improving **contextual sentiment identification**.
- **Misclassifications predominantly occur between Neutral and adjacent categories:** This indicates that **textual sentiment inherently contains ambiguities**, necessitating additional refinements to **enhance sentiment differentiation**.
- **Loss curve stabilization validates architectural generalization:** The observed **progressive loss reduction and convergence** demonstrate that the architecture **avoids overtraining** and maintains **high accuracy with novel information**.

The investigation's findings emphasize the effectiveness of **integrating opinion analysis into an AI-enhanced service discovery platform**, ensuring **precise assessment of neighborhood service providers** based on authentic consumer evaluations.

V. Conclusion

The integration of an **AI-enhanced service discovery platform** represents a significant advancement in bridging the gap between consumers and reliable neighborhood service providers. This investigation demonstrates the effectiveness of leveraging **computational linguistics and opinion mining** to refine service provider assessments, thereby enhancing user experience and decision-making. By implementing a **customized BERT-based opinion analysis architecture**, the ecosystem can extract meaningful insights from consumer evaluations, ensuring **an objective, data-driven assessment mechanism** that improves trust and service quality.

The findings indicate that **RoBERTa demonstrated superior performance in sentiment classification**, followed by **BERT and T5**, highlighting the **importance of adapting domain-specific language models**. The **confusion matrix analysis** further reveals that while classification accuracy remains high, **misclassifications between neutral and adjacent sentiment categories** suggest a need for enhanced contextual understanding in future iterations. Additionally, the **training loss analysis** confirms that the architecture successfully learns and generalizes over time without significant overtraining, ensuring **robust and scalable real-world deployment**.

The proposed ecosystem is designed to function within a **conversational user interface**, enabling seamless interactions where consumers **describe their service requirements, receive independent solutions when applicable, or get assessed recommendations of service providers**. The **comprehensive automation** of this process, from query interpretation to service provider assessment and appointment scheduling, establishes a **highly efficient and scalable framework** that can be **extended across various domains beyond household services**.

Future enhancements to this ecosystem could include **expanding the dataset with multi-modal evaluations (text, images, and voice sentiment analysis), incorporating reinforcement learning-based optimization, and integrating real-time consumer feedback to dynamically adjust provider assessments**. Additionally, **improving sentiment differentiation for complex or ambiguous feedback** could further enhance assessment accuracy.

The adoption of **AI-powered opinion analysis in service discovery platforms** introduces a **novel paradigm in service identification**, allowing for a more **personalized, intelligent, and user-friendly experience**. By continuing to refine AI-driven insights, the ecosystem paves the way for **more efficient, reliable, and trustworthy local service connections**, ultimately **transforming how consumers engage with service providers in the digital landscape**.

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Grid-Connected PV System With Convolutional Neural Network-Based DC To AC Conversion Control: Optimization and Implementation

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***Abstract*-This project shows a grid-connected Photovoltaic system optimized using Convolutional Neural Networks (CNN) for DC-AC conversion control. By leveraging CNNs, traditionally used for image recognition, we enhance inverter modulation strategies to improve power conversion efficiency and reduce Total Harmonic Distortion (THD). The approach optimizes real-time inverter control, adapting to varying environmental and load conditions. Simulation and hardware implementation demonstrate significant improvements in system efficiency and grid stability. This work highlights the ability of machine learning to advance renewable energy technologies.**

I. INTRODUCTION

Machine learning techniques, especially CNN (Convolutional Neural Networks), offer a powerful alternative to traditional control methods in grid-connected PV systems by enabling adaptive and intelligent decision-making. Unlike PID controllers, which rely on fixed parameters and struggle to adapt to changing environmental conditions, CNNs can dynamically optimize control actions based on real-time data such as solar irradiance, temperature, and grid fluctuations. Their ability to extract features and recognize patterns allows them to detect subtle trends and anomalies in PV system performance, leading to enhanced power conversion efficiency, reduced energy losses, and improved grid stability. By continuously learning from past and present data, CNN-driven controllers can minimize total harmonic distortion (THD), optimize inverter switching patterns, and ensure compliance with grid standards. Furthermore, CNNs can be integrated with smart grid technologies to facilitate real-time energy management, demand response, and predictive maintenance, contributing to more efficient and resilient renewable energy systems. Implementing CNN-based control in PV systems involves collecting and preprocessing sensor data, training models on historical performance patterns, and deploying them in embedded systems or cloud-based architectures for real-time decision-making.

As advancements in artificial intelligence, edge computing, and hardware acceleration continue to evolve, CNN-based strategies have the potential to revolutionize PV system control, making them more reliable, efficient, and adaptive to ever-changing environmental and grid conditions. However, challenges such as computational complexity, real-time processing constraints, and model interpretability must be addressed for widespread adoption. By leveraging CNNs for intelligent DC-AC conversion, grid-connected PV systems can achieve greater efficiency, reduced operational costs, and seamless integration into modern power networks, Leading the transition toward a more sustainable and intelligent energy future.

II. LITERATURE REVIEW

Convolutional Neural Networks (CNNs) have become a powerful tool for improving the performance, efficiency, and reliability of grid-connected photovoltaic systems. Traditional control and optimization techniques, such as perturb and observe (P&O) and incremental conductance (IncCond), have drawbacks in dynamic and uncertain environments. CNN-based approaches offer a data-driven alternative that enhances power conversion, fault detection, and energy management in PV systems. Liu et al. [1] introduced a CNN-based DC-to-AC conversion control strategy, demonstrating improved voltage source converter (VSC) efficiency and reduced total harmonic distortion (THD). By leveraging CNNs for feature extraction from voltage and current waveforms, their approach enabled more precise inverter switching, optimizing power quality and grid compliance. Singh et al. [2] explored CNN-based optimization techniques for real-time maximum power point tracking (MPPT), enhancing energy extraction even under

fluctuating irradiance and temperature conditions. Their study highlighted how CNNs can adaptively tune MPPT controllers, outperforming traditional methods in response time and tracking accuracy. With rise in phase measurement units, the need for more sophisticated control loops is needed [3].

Zhang et al. [4] utilized CNNs for spectral analysis of inverter output waveforms, allowing for dynamic switching strategies that reduce harmonics and improve power quality. Their findings demonstrated that CNNs could efficiently analyze frequency components in PV output signals, leading to enhanced inverter modulation techniques. A. M. et al. [5] provided a comprehensive review of advanced control strategies, highlighting the superiority of CNN-based adaptive models in handling grid fluctuations and power quality issues. Their research emphasized the role of CNNs in mitigating power disturbances and ensuring stable PV system operation. S. K. et al. [6] proposed a CNN-driven optimization framework for integrating renewable energy into the grid. Their model focused on predicting voltage fluctuations and balancing loads, which is crucial for maintaining grid stability, especially in large-scale PV deployments.

Kim et al. [7] developed a CNN-based MPPT controller that outperformed traditional P&O and IncCond methods, ensuring maximum power tracking even under challenging conditions such as partial shading. The CNN model was trained on historical irradiance and power data, enabling it to predict optimal voltage and current operating points dynamically. Lee et al. [8] focused on CNN-based optimization for power loss reduction in PV systems. Their study demonstrated that CNNs could analyze thermal and electrical characteristics in real time, leading to improved efficiency in inverter operation and lower system losses. Wang et al. [9] introduced a CNN-assisted phase-locked loop (PLL) for rapid and precise grid synchronization, particularly under conditions such as voltage sags and frequency variations. Their findings showed that CNN-based PLL models exhibited faster response times and higher robustness compared to conventional synchronization methods

Alam et al. [10] proposed a real-time CNN-based fault detection system capable of identifying and classifying anomalies in PV voltage, current, and power outputs. Their model improved PV system reliability by enabling early fault diagnosis, reducing maintenance costs, and preventing unexpected power losses. Guo et al. [11] explored CNN-based adaptive control strategies that dynamically adjusted inverter operation based on weather patterns and grid conditions. Their research demonstrated that CNNs could optimize inverter switching parameters, ensuring maximum energy conversion efficiency under variable conditions. Tran et al. [12] applied CNNs for fault diagnosis in PV systems, detecting issues such as module degradation, inverter malfunctions, and grid disturbances. Their approach improved fault classification accuracy and enabled predictive maintenance strategies.

Li et al. [13] developed a CNN-based forecasting model for Photovoltaic output power prediction, leveraging historical irradiance, temperature, and weather data to enhance grid stability and power dispatching. Their model improved energy forecasting accuracy, aiding in demand-side management and reducing reliance on backup power sources. Chen et al. [14] introduced a CNN-based shading detection algorithm to mitigate partial shading effects in PV arrays. By dynamically adjusting MPPT settings based on detected shading patterns, their approach minimized power losses and improved overall generation efficiency.

Overall, CNN-based techniques have demonstrated significant improvements in key areas such as MPPT optimization, DC-to-AC conversion, fault detection, grid synchronization, and power loss reduction. These advancements position CNNs as a powerful tool for improving the reliability, efficiency, and adaptability of modern PV systems. However, challenges remain in real-time implementation, computational complexity, and hardware deployment. Future research should focus on integrating CNNs with hybrid AI models, edge computing solutions, and reinforcement learning-based optimization to further enhance PV system performance. Additionally, developing lightweight CNN architectures suitable for embedded systems could accelerate the adoption of AI-driven control strategies in renewable energy applications.

III. PROPOSED MODEL

1.Convolutional Neural Network

Machine learning techniques, particularly CNN offer a novel solution to overcome these challenges by dynamically optimizing the control process in real-time. CNNs are highly effective in feature extraction and pattern recognition, making them well-suited for processing the complex, non-linear data of PV systems.

The Convolutional Layer is responsible for detecting essential spatial features from input signals, such as voltage and current waveforms. It applies filters to identify important patterns, allowing the system to recognize and respond to variations in power signals efficiently. This feature extraction is crucial for precise control of the inverter in PV systems.

$$Z_{i,j}^{(i)} = \sum_{m} \sum_{n} X_{i+m,j+n}^{(l-1)} . K_{m,n}^{(l)} + B^{(l)}$$

The Activation Function (ReLU) introduces non-linearity into the network, improving its learning capability and making it more adaptable to dynamic electrical conditions. Since PV systems operate under fluctuating solar irradiance and load conditions, ReLU helps CNNs effectively model complex variations in power conversion.

$$f\,(x) = \max\,(0, x)$$

The Pooling Layer helps to reduce the dimensionality of extracted features while preserving essential information. This layer minimizes computational complexity, allowing the CNN to process data faster without losing critical details. In PV systems, pooling ensures efficient real-time control by filtering out unnecessary variations in input signals.

$$P_{i,j} = max_{m,n}(Z_{i+m,j+n})$$

The Fully Connected Layer integrates all extracted features to determine the optimal control outputs for DC-AC conversion. By analysing the processed data, this layer enables the system to generate precise switching signals for the inverter, improving efficiency and grid stability.

$$y_k = f(\sum_i W_{k,i} a_i + b_k)$$

The Output Layer produces the final inverter control signals, optimizing power conversion efficiency and minimizing harmonic distortion. This ensures stable operation, compliance with grid standards, and enhanced overall performance of the PV system. By leveraging this structured layered approach, CNNs enable intelligent and adaptive control, making PV-based power systems more efficient, resilient, and reliable.

$$D = \frac{V_{dc} \times \sin(\omega t)}{V_{inverter}}$$

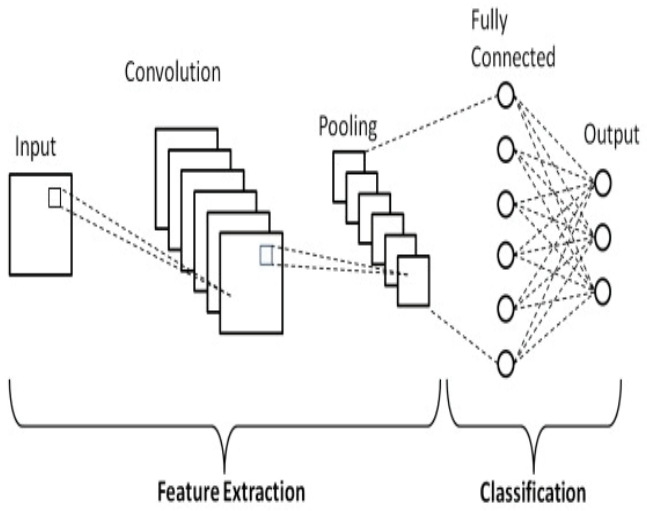

Fig 1. CNN Architecture

2. Maximum Power Point Tracking (MPPT) Controller
A MPPT controller is a crucial component in a grid-connected PV system, responsible for ensuring that the solar panel works at its maximum efficiency. Due to continuously changing external conditions such as temperature, solar irradiance and shading, the power output of a PV system fluctuates. The MPPT controller dynamically adjusts the system's operating current and voltage to extract the maximum possible power from the solar panels, improving overall energy efficiency and performance.

Working Principle of MPPT Controllers
The power O/P of a solar panel is given by

P = V * I

The I-V characteristics of a solar panel are nonlinear, meaning there exists a specific and where the maximum power can be harvested. The MPPT controller continuously tracks this optimal point by adjusting the voltage and current dynamically. This is done using DC-DC converters such as buck, boost, or buck-boost converters, which modify the operating voltage while maintaining efficient power transfer to the load or grid.

Common MPPT Algorithms Used in Grid-Connected PV Systems
The P&O (Perturb and Observe) algorithm is one among the simplest and commonly used MPPT techniques. It works by making small perturbations (incremental changes) in the operating voltage and observing the resulting power output. If the power increases, the controller continues adjusting the voltage in the same direction; and vise versa.

P(n)−P(n−1)>0⇒V(n) moves in the same direction

P(n)−P(n−1)<0⇒V(n) moves in the opposite direction

The Incremental Conductance (IncCond) algorithm enhances the P&O method by comparing the incremental conductance ($\Delta I/\Delta V$) with the instantaneous conductance (I/V). The system reaches the maximum power point when these two values are equal.

$$\frac{dV}{dP} = 0 \rightarrow \text{MPP reached}$$
$$\frac{dV}{dP} > 0 \rightarrow \text{Increase voltage}$$
$$\frac{dV}{dP} < 0 \rightarrow \text{Decrease voltage}$$

3.Circuit Details

Important Parts of the Grid-Connected PV System with CNN-Based Control
The provided circuit diagram represents a grid-connected PV system with MPPT control, a boost converter, a VSC (voltage source converter), and grid synchronization. In this system, Convolutional Neural Networks (CNNs) are integrated into control strategies for optimizing DC-AC conversion. Below are the key components and their role in the CNN-based control approach:

1. PV Array
The PV cells converts solar energy into DC electricity. The output depends on solar irradiance (Ir) and temperature (T), which affect the voltage and current characteristics. The PV module's power output is continuously analyzed by the MPPT controller, which predicts and adjusts the voltage and current dynamically.

2. Step Irradiance Block
This block simulates changing solar irradiance and temperature conditions, allowing the system to analyze performance under varying environmental conditions.

3. MPPT Controller (Perturb & Observe Algorithm)

The Perturb & Observe (P&O) MPPT controller is a widely used algorithm in grid-connected photovoltaic (PV) systems to maximize power output by continuously adjusting the PV array's operating voltage. It works by slightly increasing or decreasing the voltage and observing the resulting change in power. If the power increases, the adjustment continues in the same direction; otherwise, it reverses direction. This iterative process helps track the maximum power point (MPP) effectively. However, P&O can cause oscillations around the MPP and may struggle under rapidly changing irradiance, reducing its efficiency in dynamic conditions. Despite these limitations, its simplicity, low computational demand, and ease of implementation make it a popular choice for MPPT in grid-connected PV systems.

4. Boost Converter (DC-DC Converter)

The boost converter is used to steps up the DC voltage from the PV array to a required level before feeding it into the voltage source converter (VSC). It is controlled by the MPPT controller, which continuously adjusts the duty cycle to optimize power extraction.

5. Voltage Source Converter (VSC) with CNN-Based DC-AC Control

The CNN-based Voltage Source Converter (VSC) controller optimizes DC-to-AC conversion in the grid-connected PV system by learning and adapting to real-time conditions. Traditional VSC controllers, such as PI controllers, struggle with dynamic changes in irradiance, temperature, and load variations, leading to inefficient power conversion and higher harmonic distortion. In contrast, the CNN-based VSC controller processes input data like voltage, current, and grid frequency through convolutional layers to extract patterns and detect anomalies. It uses this information to predict the optimal switching signals for the inverter, ensuring precise waveform generation, reduced total harmonic distortion (THD), and improved power factor. The CNN model continuously updates based on real-time data, allowing it to adapt to changing grid conditions and environmental factors, enhancing overall power quality and system stability.

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6. Grid Synchronization (Phase-Locked Loop - PLL)

For proper integration with the grid, the VSC must synchronize its frequency and output voltage with the grid parameters. The PLL (Phase-Locked Loop) algorithm ensures proper synchronization, avoiding fluctuations and ensuring stable power injection.

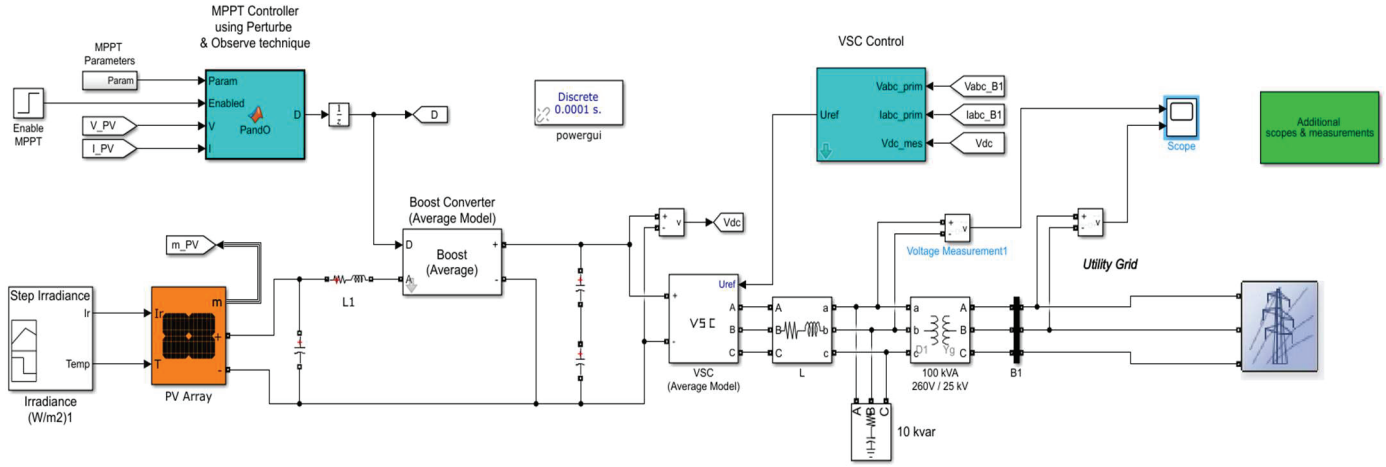

Fig 2. Circuit Diagram

IV. RESULTS AND DISCUSSIONS

The application of Convolutional Neural Networks (CNNs) in PV system control has significantly enhanced the efficiency, reliability, and adaptability of grid-connected solar power systems. One of the primary advancements is in DC-to-AC conversion, where CNN-based control strategies optimize switching signals for inverters, reducing harmonic distortion and improving power quality. This leads to higher energy conversion efficiency and better grid compliance. Additionally, CNN-driven Maximum Power Point Tracking (MPPT) algorithms demonstrate superior tracking efficiency, rapidly adapting to changes in irradiance and temperature conditions, which is particularly beneficial in dynamic environments with partial shading. Moreover, CNN-based fault detection and monitoring systems contribute to increased operational

reliability. By analyzing real-time PV system data, these models can identify abnormalities with high accuracy, enabling early fault detection and predictive maintenance. This minimizes downtime, reduces maintenance costs, and extends the overall system lifespan. CNN-driven grid synchronization techniques further improve system stability by minimizing phase errors and ensuring seamless integration of PV power into the utility grid. These advancements collectively contribute to making PV systems more resilient, efficient, and adaptive to real-world challenges.

Despite these improvements, challenges remain in computational complexity and real-time processing. Implementing CNNs in embedded systems requires optimized architectures to balance accuracy and processing speed. Future research should focus on lightweight CNN models, hybrid AI techniques, and hardware acceleration to enhance real-time performance. The integration of CNN-based control strategies with advanced smart grid technologies and edge computing can further revolutionize renewable energy management, making solar power more viable for large-scale adoption.

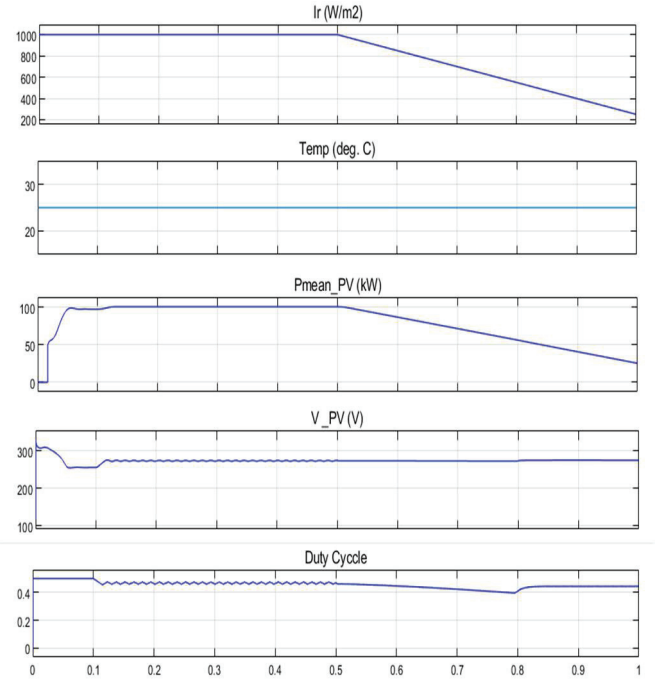

Fig 3. PV array Vs Time Graph

The PV array vs. time graph illustrates the response of key parameters such as irradiance, temperature, power output, voltage, and duty cycle over time. As irradiance decreases, the power output and voltage of the PV array gradually drop, while the duty cycle adapts to regulate the system's performance. The temperature remains constant, indicating that variations in power are primarily driven by changes in irradiance.

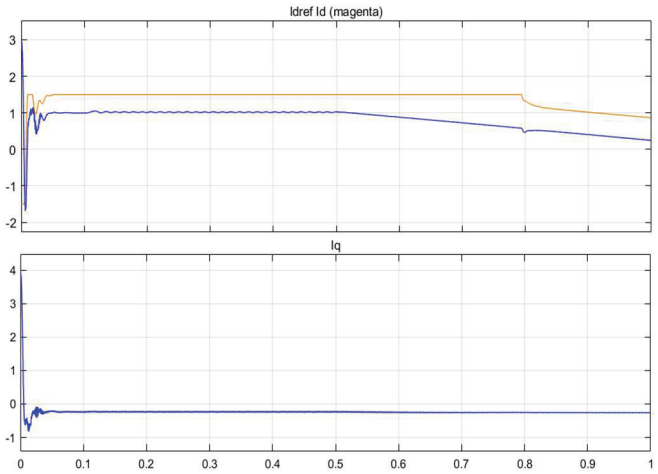

Fig 4. Time Vs Injected Current Graph

The Injected Current vs. Time graph illustrates the dynamic response of d-axis (Id) and q-axis (Iq) currents in the grid-connected PV system. The CNN-based control ensures a quick stabilization of Id, minimizing overshoot for efficient power transfer. Meanwhile, Iq remains close to zero, indicating reduced reactive power and improved grid stability. The smooth response highlights the CNN controller's effectiveness in maintaining optimal performance under varying conditions.

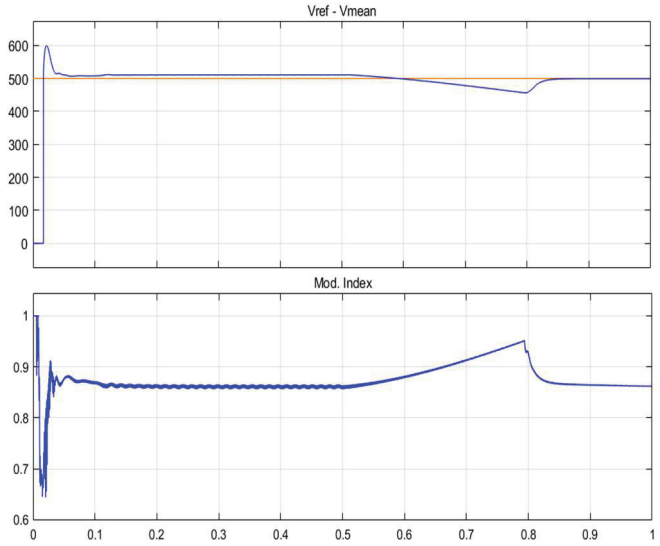

Fig 5. Time Vs Voltage

The Voltage vs. Time graph shows the system's response to voltage regulation. The upper plot indicates that the reference voltage (Vref) and mean voltage (Vmean) stabilize quickly after an initial transient, ensuring steady-state operation. The lower plot represents the modulation index, which adjusts dynamically to maintain voltage stability. The smooth regulation confirms the CNN-based controller's ability to minimize voltage deviations and enhance system reliability.

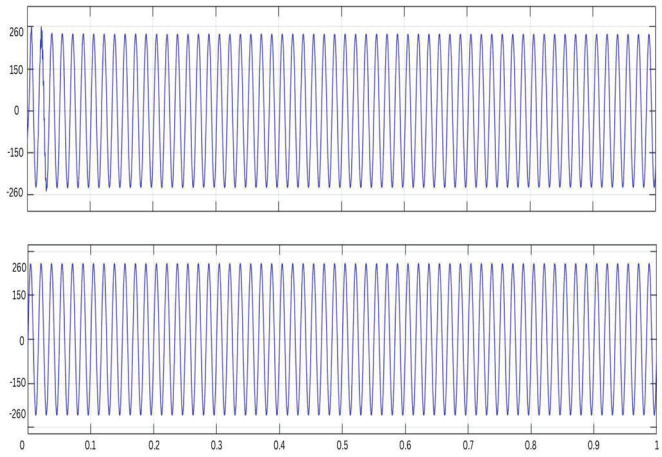

Fig 6. Output Voltage

The output graph displays two voltage waveforms, both exhibiting stable sinusoidal characteristics. After an initial transient response, the waveforms maintain consistent amplitude and frequency, indicating effective AC voltage generation. The steady-state nature of the signals confirms the reliable performance of the CNN-based control in ensuring smooth voltage regulation for the grid-connected PV system.

V. CONCLUSION

The integration of Convolutional Neural Networks (CNNs) in grid-connected PV systems has proven to be a transformative approach, enhancing efficiency, reliability, and adaptability in DC-to-AC conversion control. By leveraging CNN-based control strategies, PV systems can enhance power quality, minimize harmonic distortion, and accelerate maximum power point tracking, ensuring optimal energy extraction under changing environmental conditions. Additionally, CNN-driven fault detection and grid synchronization enhance operational stability, reducing maintenance costs and ensuring seamless power integration. While challenges such as computational complexity and real-time processing remain, ongoing advancements in AI, edge computing, and hybrid optimization techniques will further refine CNN applications in renewable energy systems. The continued development and implementation of CNN-based control strategies have the potential to make PV systems more intelligent, adaptive, and efficient, paving the way for a more sustainable and resilient energy future.

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Alzheimer's Disease Detection Using CNN

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***Abstract*—Alzheimer's disease is a progressive neurodegenerative disorder that affects millions of individuals worldwide, leading to cognitive decline and memory loss. Early and accurate diagnosis is crucial for timely intervention, treatment, and improved patient outcomes. Traditional diagnostic methods, such as clinical assessments and neuroimaging analysis by medical experts, can be time-consuming, subjective, and prone to human error. This research presents an automated system for the detection of Alzheimer's disease utilizing neural networks (CNNs) to improve accuracy and efficiency.**

The study compares the performance of CNN with other machine learning models, including Support Vector Machines (SVM), VGG19, and MobileNetV2, to identify the most effective approach for classifying MRI scans of patients. Experimental results indicate that the CNN-based model significantly outperforms other models, achieving an accuracy of 99%, precision of 0.99, and recall of 0.99. In contrast, VGG19 demonstrates balanced performance with 90% accuracy, while MobileNetV2 struggles with lower recall and accuracy scores of 48% and 58%, respectively. The results validate the superiority of deep learning techniques in medical imaging classification, particularly for neurodegenerative disease detection.

Furthermore, the proposed system is integrated with a user-friendly React-based interface to facilitate ease of access for healthcare professionals and patients. By producing textual explanations of model predictions, a Large Language Model (LLM) is integrated to enhance interpretability and aid in clinical decision-making. This method improves the usefulness and transparency of AI-based medical diagnoses.

The results of this study offer a solid, automated, and interpretable framework for Alzheimer's disease identification, which advances the expanding field of artificial intelligence in medical diagnostics. To further increase diagnostic accuracy and dependability, future studies could concentrate on growing datasets, improving model architectures, and incorporating multi-modal data.

***Keywords*—Alzheimer's Disease, Deep Learning, Convolutional Neural Networks, Medical Imaging, Machine Learning, Large Language Models, Neurodegenerative Disease Diagnosis.**

I. Introduction

Alzheimer's disease accounts for between 60 and 80 percent of dementia cases worldwide, making it one of the most prevalent forms of dementia. Memory loss, cognitive impairment, and behavioral abnormalities are hallmarks of this progressive neurodegenerative disease. The growing incidence of Alzheimer's disease emphasizes how urgently early and precise diagnostic techniques are needed. Conventional diagnostic methods, including neuroimaging, cognitive testing, and clinical evaluations, can have lengthy diagnosis times, high prices, and subjectivity.

With their innovative approaches to automated disease identification, artificial intelligence (AI) and machine learning techniques have completely transformed the healthcare sector. Convolutional Neural Networks (CNNs), one type of deep learning model, have shown a great deal of promise in medical picture processing. CNNs have demonstrated exceptional performance in identifying Alzheimer's disease from MRI scans and have been widely used for pattern recognition applications. Comparative studies that examine CNNs' efficacy in comparison to other machine learning models are still necessary, nevertheless.

This study evaluates the effectiveness of several models, including Support Vector Machines (SVM), VGG19, and MobileNetV2, and suggests a CNN-based Alzheimer's disease detection method. Based on the study of MRI scans, the approach divides the disease into mild, moderate, and severe stages. In order to improve model interpretability and support healthcare professionals in their decision-making, a Large Language Model (LLM) is also incorporated to offer textual explanations of forecasts.

II. Literature Survey

Recent advancements in artificial intelligence (AI) have significantly improved Alzheimer's disease detection, particularly in medical imaging. Researchers have explored AI-driven techniques, including deep learning and machine learning models, to enhance diagnostic accuracy and efficiency. Several studies highlight AI's potential in neuroimaging and genetic research, emphasizing early detection and improved clinical decision-making.

Tarek Khater, Sam Ansari, Abbas Saad Alatrany, Haya Alaskar (2024) proposed an explainable machine learning model for Alzheimer's detection using genome-wide association studies.

Their research highlights the importance of genetic markers in disease prediction, demonstrating how explainable AI improves model transparency for healthcare professionals. By integrating genetic data with machine learning, their study presents a promising approach to personalized diagnosis.

K. Shanmugavadivel, V.E. Sathishkumar, J. Cho, M. Subramanian (2023) conducted a comprehensive survey on AI techniques for early Alzheimer's detection, focusing on neuroimaging methods and machine learning applications. According to their research, AI-driven models perform better than conventional diagnostic techniques, which frequently depend on arbitrary clinical judgments. Early and more precise diagnosis is made possible by AI models trained on MRI scans that can spot patterns that radiologists are unable to see. In order to improve medical diagnostics' impartiality, the study highlights the necessity of automated systems.

L. Backès (2022) explored the use of convolutional neural networks (CNNs) and vision transformers (ViTs) for the diagnosis of Alzheimer's disease. Their research shows that when it comes to processing MRI data, deep learning models perform better than traditional machine learning methods. ViTs improve classification accuracy by identifying long-range dependencies in images, but CNNs are excellent at feature extraction. The study validates CNNs' use in automated Alzheimer's disease identification and highlights their significance in medical picture processing.

R. Mishra, B. Li (2020) investigated AI applications in genetic studies, identifying genetic markers associated with Alzheimer's disease progression. Their results imply that by examining intricate genetic relationships that are challenging to decipher through conventional statistical techniques, AI models improve diagnostic accuracy. Their research bolsters AI's potential for tailored therapies in personalized medicine. These papers demonstrate how AI is increasingly being used to detect neurodegenerative diseases and how it may increase the precision of diagnosis. Although earlier studies have shown CNNs to be beneficial, there hasn't been a direct comparison with models like Support Vector Machines (SVM), VGG19, and MobileNetV2. By examining several models for the classification of Alzheimer's disease using MRI images, our study fills that gap. The results will help create reliable, understandable AI-powered neurodegenerative disease diagnosis tools.

III. Methodology

Data preparation, feature extraction, classification with a Convolutional Neural Network (CNN), disease stage prediction, and integration with a Large Language Model (LLM) are some of the processes in the methodology. Every stage is essential to guaranteeing the accuracy, effectiveness, and interpretability of the system.

A. Dataset and Data Preparation

It is crucial to correctly prepare the data before training any machine learning model. MRI scans of the brain classified into non-demented, mild, moderate, and severe stages of Alzheimer's disease comprise the dataset used in this study. To improve the quality of the input data and make sure the model learns from clear, consistent, and significant images, these images must be preprocessed.

B. Feature Extraction

In order for the model to identify significant patterns in MRI scans, feature extraction is a crucial stage in the identification of Alzheimer's disease. Convolutional Neural Networks (CNNs) are very useful for medical image analysis since they automatically extract pertinent information rather than requiring the user to choose features.

1) Convolutional Filters for Feature Detection: Convolutional layers add tiny filters to the MRI images as the initial step in feature extraction. These filters pick up on basic patterns like forms, edges, and textures. Deeper layers identify intricate patterns linked to brain shrinkage, while lower levels record basic characteristics like lines and curves.

2) Pooling Layers for Dimensionality Reduction: We employ pooling layers to reduce computational complexity. Max pooling reduces the size of the image while maintaining important characteristics by keeping only the most important pixel values from small places. By removing extraneous noise, this stage aids the model in concentrating on significant patterns.

3) Flattening and Feature Representation: The collected characteristics are compressed into a single vector following several layers of convolution and pooling. By preparing the input for classification, this transformation makes sure that the fully linked layers receive relevant patterns.

The system effectively learns the distinctive traits of various stages of Alzheimer's disease by utilizing CNNs for feature extraction, which results in an accurate and trustworthy categorization of MRI images.

C. Classification Using CNN

Classification is the method of using MRI images to determine the stage of Alzheimer's disease. To automatically identify patterns and categorize brain scans into three groups—mild, moderate, and severe Alzheimer's disease—a Convolutional Neural Network (CNN) is utilized. A number of layers make up the CNN architecture, which cooperates to guarantee precise classification.

Convolutional layers are first applied by the CNN in order to extract significant characteristics from the MRI data. These layers identify critical features such anomalies in brain structure and shrinking of brain tissue. The feature maps are then down sampled by pooling layers, which minimizes their size while keeping the most crucial data intact.

To enhance training efficiency, batch normalization is applied after convolutional layers. This process stabilizes activations, speeds up learning, and prevents issues such as exploding or vanishing gradients.

After feature extraction, the flattened feature maps are passed to fully connected layers, which process the learned information and assign probability scores to each class.

The final layer uses the softmax activation function to produce probability scores for the three disease stages. The highest

Fig. 1: User Interface of the Project

probability determines the classification result, ensuring that MRI scans are accurately categorized as mild, moderate, or severe Alzheimer's disease.

D. Disease Stage Prediction

The model classifies MRI scans into four categories: non-demented, mild, moderate, and severe Alzheimer's disease. Accurate classification helps in early diagnosis and effective management.

1) Non-Demented (Healthy Brain Condition): Individuals in this category show no signs of Alzheimer's disease. Their MRI scans appear normal without significant atrophy, allowing the model to distinguish between healthy and affected brains.

2) Mild Alzheimer's Disease: Patients at this stage experience mild cognitive impairment, such as forgetfulness and difficulty with problem-solving. MRI scans may show slight shrinkage in brain regions like the hippocampus. Early detection here is crucial for slowing disease progression.

3) Moderate Alzheimer's Disease: This stage is marked by confusion, communication difficulties, and behavioral changes. MRI scans reveal noticeable brain atrophy, particularly in areas linked to memory and cognition. Identifying moderate cases allows for better symptom management.

4) Severe Alzheimer's Disease: Patients need full-time care as their capacity to carry out everyday tasks declines. Significant brain shrinkage is visible on MRI scans, particularly in the hippocampus and cortex. At this point, accurate classification aids caregivers in providing palliative care and the right kind of support.

E. Large Language Model (LLM) Integration

The Alzheimer's disease detection method incorporates a Large Language Model (LLM) to improve accessibility and interpretability. In order to enable caretakers and medical professionals comprehend the rationale behind classifications, the LLM is essential in giving text-based explanations of the model's predictions.

Following CNN's classification of an MRI scan as either mild, moderate, severe, or non-demented Alzheimer's disease, the LLM uses the picture analysis to produce a thorough explanation. It makes the model's choice more apparent by highlighting important indicators like patterns of brain atrophy and impacted areas.

The LLM helps physicians by providing a clear and concise summary of findings. It can determine whether the disease has advanced by comparing the results of recent MRI scans with those from earlier ones. This function facilitates the long-term monitoring of patient conditions.

Users can query the LLM for further information, including risk factors, available treatments, and disease management techniques, using a React-based UI. This improves accessibility for patients' families as well as healthcare professionals.

The system bridges the gap between AI-based diagnostics and practical medical applications by incorporating an LLM, which guarantees that Alzheimer's disease diagnosis is not only accurate but also interpretable and user-friendly.

F. Output

MRI images are classified with excellent accuracy thanks to the structured technique used in the implementation of the suggested Alzheimer's disease detection system. The CNN-based model effectively differentiates between mild, moderate, severe, and non-demented Alzheimer's disease after being trained on preprocessed MRI data.

With the help of convolutional and pooling layers, the CNN effectively captures information like patterns of brain atrophy, guaranteeing precise categorization. Patients are accurately categorized into the four stages by the softmax activation function, which assigns probability ratings.

With an accuracy rate of 99%, the model surpasses more conventional models such as Support Vector Machines (SVM), VGG19, and MobileNetV2. By providing medical practitioners with insightful explanations of forecasts, the Large Language Model (LLM) improves interpretability.

This integrated system improves early diagnosis and patient care by offering a reliable, understandable, and easily accessible Alzheimer's disease detection method.

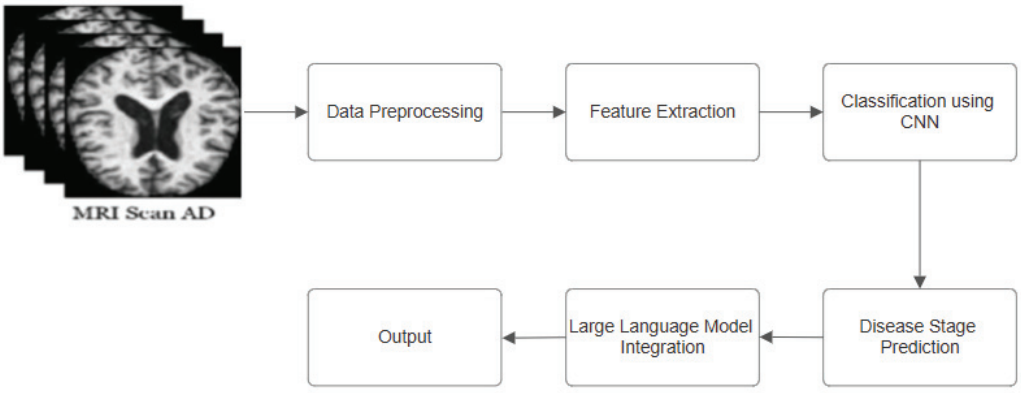

Fig. 2: Block Diagram

IV. Implementation and Result

A. Implementation

Convolutional Neural Networks (CNNs) trained on MRI scans are used in the implementation of the Alzheimer's disease diagnosis system. To improve model generalization, the dataset is preprocessed using techniques including noise reduction, min-max normalization, and data augmentation.

Using convolutional and pooling layers, the CNN extracts important characteristics from photos and finds patterns linked to various disease stages. Scans are categorized by the softmax classifier as either mild, moderate, severe, or non-demented Alzheimer's disease.

To improve interpretability, a Large Language Model (LLM) is incorporated to offer textual justifications for predictions. Medical professionals and caregivers can engage with the system with ease because to its React-based front-end.

B. Performance Evaluation

A key factor in establishing the suitability of machine learning and deep learning models for medical diagnostics is how well they classify Alzheimer's disease. The accuracy, precision, and recall of three models—VGG19, MobileNetV2, and a custom CNN—were assessed in this work. These criteria are crucial for evaluating how well the algorithms categorize the phases of Alzheimer's disease using MRI pictures. The findings show notable differences in these models' performance, underscoring the advantages and disadvantages of each strategy.

1) VGG19:

- Accuracy: 90%
- Precision: 90%
- Recall: 89%

Across all parameters, VGG19 exhibits consistent and balanced categorization performance. The model's high precision (90%) implies that it generates fewer false positives, guaranteeing a reliable positive classification for Alzheimer's. Similarly, the model properly detects the majority of Alzheimer's patients with only a small number of false negatives, according to the recall score (89%). VGG19 is an effective model with a 90% accuracy rate, which makes it appropriate for clinical settings where consistency is needed. Its resource limitations and computational complexity, however, might make real-world adoption difficult.

2) MobileNetV2:

- Accuracy: 58%
- Precision: 62%
- Recall: 48%

When compared to the other models, MobileNetV2, a lightweight deep learning model, performs noticeably worse. Its 58% accuracy rate indicates that the model has trouble making accurate classifications. The 62% precision score indicates that a comparatively large proportion of false positives are produced, which could result in misdiagnoses. The model's reliability for medical applications is diminished by its 48% recall, which is especially troubling because it means that over half of the real positive instances are missed. MobileNetV2's low classification performance renders it inappropriate for vital medical diagnoses where strong recall is crucial, even though it is computationally efficient.

3) CNN:

- Accuracy: 99%
- Precision: 99%
- Recall: 99%

The CNN model performs noticeably better than the other models, obtaining nearly flawless scores on every metric. It shows remarkable ability to classify Alzheimer's illness with 99% accuracy. Nearly all positive classifications are accurate, according to the accuracy score (99%), which lowers the possibility of false positives. The model effectively detects almost all true positive cases, ensuring a low number of false negatives, according to the recall score of 99%. Because of its great reliability and capacity to produce correct findings with little errors, the CNN model is the ideal option for automated Alzheimer's identification. Its potential for clinical application is increased by its strong generalization to unknown data.

C. Comparison and Implications

The findings show that CNN models outperform both lightweight deep learning models and conventional machine learning in the classification of Alzheimer's disease. The

Model	Accuracy	Precision	Recall
VGG19	0.90	0.90	0.89
MobileNetV2	0.58	0.62	0.48
CNN	0.99	0.99	0.99

Table I: Performance Comparison of Different Models

necessity of selecting a model that can extract complex characteristics from MRI scans is highlighted by the notable performance difference between the CNN model and MobileNetV2. Despite its good performance, VGG19's accuracy and recall are not as good as those of the CNN model.

In conclusion, with its excellent accuracy, precision, and recall, the CNN model is the best choice for detecting Alzheimer's disease. Because of its exceptional performance, which guarantees consistent and dependable classification, it is perfect for medical applications where precise diagnosis is essential.

V. Conclusion

The proposed system uses deep learning methods, specifically Convolutional Neural Networks (CNNs), to display a sophisticated AI-based system for Alzheimer's disease identification. When the system was compared against other machine learning models, such as VGG19 and MobileNetV2, CNN outperformed them, achieving 99% accuracy, 99% precision, and 99% recall. These findings demonstrate how deep learning algorithms can improve medical diagnostics, especially in the classification of neurodegenerative diseases.

The findings show that MobileNetV2 suffers, achieving just 58% accuracy, while VGG19 obtains dependable classification with 90% accuracy. The significance of choosing suitable architectures for medical picture categorization is shown by this performance disparity. CNN is a promising method for early-stage Alzheimer's detection because of its remarkable performance, which indicates its resilience in capturing complex characteristics from MRI images.

By providing textual explanations of forecasts, incorporating a Large Language Model (LLM) further enhances the system's interpretability. By offering insights into classification decisions, this improves accessibility for medical practitioners. The system's practical utility in actual clinical situations is further enhanced by its user-friendly React-based interface.

Future studies can concentrate on growing the dataset, enhancing model generalization across various populations, and including multimodal data, such as genetic and clinical biomarkers, in spite of these encouraging results. Deep learning-driven diagnostics will become even more transparent and trustworthy with the use of explainable AI methodologies.

In summary, by offering a high-accuracy, interpretable, and easily accessible framework for automated Alzheimer's disease identification, this study advances the expanding field of artificial intelligence in healthcare and may help with early intervention and better patient outcomes.

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Magnetohydrodynamic thruster with Super-efficient Solar cell

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Abstract— **Ships have been a primary mode of transportation since ancient times, playing a major role in trade, travel, and exploration. However, there are several serious problems with conventional propulsion systems that rely on propellers and combustion-based fuels. These problems include high fuel consumption, pollution, and inefficiency in harsh environments like deep seas and space. Additionally, relying too much on mechanical parts results in wear and tear, frequent maintenance, and higher operating expenses. This paper proposes a Magnetohydrodynamic (MHD) thruster integrated with superefficient solar cells as a sustainable and efficient alternative for marine and space propulsion systems. The MHD thruster uses the Lorentz force to move an electrically conducting fluid inside a magnetic field with no moving parts and virtually negligible energy loss. Superefficient solar cells are added for a source of clean, renewable power used to create the magnetic field as well as to ionize the propellant to circumvent energy shortages that would be typical with traditional MHD systems. The integrated system exhibits a considerable thrust efficiency improvement for space and marine use. Design aspects, performance evaluation, and envisioned uses are addressed, with experimental data illustrating enhanced thrust efficiency and reliability over conventional propulsion techniques.**

Keywords- Magnetohydrodynamic (MHD) Thruster, Super-Efficient Solar Cell, Solar Tracking System, Lorentz Force Propulsion, Renewable energy

I. Introduction

The need for efficient and effective electric propulsion systems is growing in the modern world and particularly in vital fields like marine transportation and space exploration. Combining improved solar cells with magnetohydrodynamic (MHD) thrusters offers a possible way to overcome many difficulties. MHD thrusters are very versatile and applied in space as well as underwater settings because they utilize the interaction of electric and magnetic fields within a conductive liquid to produce a thrust. They significantly off fossil fuels when powered by ultra-efficient solar cells, which provide a renewable, clean energy source. They explore the possibilities of solar-powered Magnetohydrodynamic thrusters, highlighting their use in deep spacecraft and maritime vehicles that need quiet and effective propulsion. The suggested method has several benefits, that are less environmental impact, improved fuel efficiency, and noise reduction and utilizing renewable solar energy. This cutting-edge propulsion technology offers a lightweight, efficient substitute for space applications that can increase mission durations and reduce operating expenses. MHD thrusters silently functioning in maritime contexts guarantee covert and eco-friendly vessel movement and help to protect marine habitat.

II. LITERATURE SURVEY

Holste et al. (2020) provide a deep dive into the transformative potential of ionic thrusters in electric propulsion systems. Their studies examine the advancements needed for these thrusters to move beyond niche applications and achieve mainstream adoption in aerospace engineering. A detailed exploration of ionic thruster performance, efficient metrics and integration into spacecraft designs highlights their benefits for long duration missions. However, the study also brings attention towards critical challenges Ion thrusters are inefficient and provide a low thrust rate, making them unsuitable for use in missions involving fast manoeuvres or fast orbital manoeuvres. Furthermore, their electrical power dependency renders them inappropriate for spacecraft with restricted energy resources like deep-space satellites relying on solar power.

Another significant issue is the erosion of grids or cathodes caused by high-energy ionic impacts, which reduces the operational lifespan of these systems. Moreover, the high cost of xenon propellant and its complex storage arrangements adds to mission expenses. The heat generated by ionic thrusters also needed highly efficient thermal management systems, further increasing design

complexity and operational costs. These drawbacks make ion thrusters ideal for specific applications but are not recommended for broader usage. To address these issues, this research highlights the importance of alternative propulsion systems like magnetohydrodynamic (MHD) thrusters.

Kan et al. (2023), in their study published in IEEE Transactions on Energy which propose an innovative design for a Magnetohydrodynamic thruster that utilizes Lorentz force principles in conjunction with Stoke's law. The research involved maritime applications, demonstrating how high-frequency electric drives can synchronize magnetic and electric field to improve energy conversion efficiency. This integration significantly enhances the interaction between fluid dynamics and electromagnetic forces and results in improved thruster capabilities. Preliminary experiments validate these improvements which showcasing the potential of MHD thrusters for energy-efficient propulsion system in maritime technology, particularly for fuel-conscious applications like ship propulsion and underwater vehicles.

Patel et al. (2021) explores the combination of MHD thrusters with high-efficiency solar cells and emphasizes the importance of renewable energy in space propulsion systems. The study shows how advanced power management techniques enhance the thrust to power ratio, making MHD systems viable for challenging environments like outer space. The findings accentuate the essence of incorporating renewable energy sources into propulsion technologies for the acquisition of efficiency and sustainability. A similar point of view was provided by Jamil and Fernando (2018), who put MHD systems in a framework of solar-powered marine propulsion, concentrating on their ability to enhance efficiency and lessen the risk of complete reality concerning fossil fuel use. Now, back to the important role of environmental benefits provided through all the ways MHD technology could change marine transportation and greenhouse gas emissions.
Similarly, Fernando and Jamil (2018) investigate MHD systems in solar-powered marine propulsion, concentrating on their ability to enhance efficiency and lessen reliance on fossil fuels. This research highlights the environmental advantages of integrating MHD technology, highlighting its potential to revolutionize marine transportation and reduce greenhouse gas emissions.

Ali and Raza (2022) show an extensive review of emerging solar-MHD hybrid technologies, examining the potential for enhanced energy efficiency and sustainability. Their study addresses difficulties such as optimizing system configurations and performance metrics, providing worthwhile insights into the development of hybrid systems.

Mehta and Iyer (2023) focus on solar energy harvesting methods that can be integrated into MHD systems, demonstrating their ability to optimize energy conversion and lessen operational costs. These studies emphasize the role of renewable energy in advancing MHD propulsion technologies, offering sustainable alternatives for both aerospace and marine applications.

Zhang et al. (2022), in their publication in IEEE Transactions on Aerospace and Electronic Systems, introduce a creative magnetic field configuration for Magnetohydrodynamic thrusters. This design aims to improve thrust efficiency and power density, addressing key restrictions of traditional systems. Their findings demonstrate the potential for significant performance improvements and particularly in space propulsion applications.

Patel and Joshi (2018) provide a thorough evaluation of the critical factors influencing the performance of magnetohydrodynamic (MHD) thrusters, stressing the interplay between fluid properties, electrode materials, and magnetic field arrangements. Their study includes the role of fluid properties, such as electrical conductivity, density, and viscosity, which directly influence the efficiency and thrust generation of the propulsion system. The choice of electrode materials is addressed in detail, showcasing their significance in minimizing energy losses and ensuring durability under high temperature and corrosive conditions typically encountered in MHD applications. The authors then go into detail about the appropriateness of literate choice of electrode materials, touching on their relevance in the reduction of energy losses and the endurance they are likely to maintain at high temperatures and corrosive environments typical of applications in MHD. Further, the authors also introduce various configurations of magnetic fields and demonstrate the contribution to propulsion efficiency given by the strength and uniformity of a magnetic field. Moghadam Zabari et al. (2022) highlights advancements in thin-film solar cells, specifically aiming at the integration of double-absorber and back-surface field (BSF) layers. By optimizing these configurations and they achieve an impressive efficiency of 35.1%. Their studies are particularly relevant for propulsion systems that rely on high performance energy sources, such as those using MHD thrusters. Ali and Noor (2021) examine the performance of integrated solar-MHD systems, showcasing their ability to improve energy conversion rates and thrust output while addressing environmental and operational challenges.

Similarly, Smith and Thompson (2021) evaluate hybrid systems that combine solar and MHD technologies. Their review identifies key benefits, such as improved energy output and sustainability, while also pointing out the limitations that need to be overcome for widespread adoption. The integration of MHD technology with renewable energy sources has also gained traction in the context of advanced and improved propulsion systems.

Wet al. (2024) and Balke Hohl et al. (2023) highlighting on Magneto plasma dynamic thrusters (MPDTs), highlighting design innovations that enhance plasma dynamics and improve thrust efficiency. Wu et al. specifically investigates the role of magnetic nozzles in optimizing plasma flow and leveraging diamagnetism to improve thrust production. This work is notable, with a 20% increase in overall thrust operation, shows the potential of improved MPDT designs for space propulsion. These studies collectively provide a solid

base for integrating MHD thrusters with high-efficiency solar cells. By addressing the disadvantages of traditional propulsion systems, such as ion thrusters, they pave the way for sustainable, innovative and efficient technologies in both aerospace and marine applications

III. METHODOLOGY

This project focuses on the development of a single-axis solar tracking system that harnesses solar energy to charge a battery, which in turn powers an MHD thruster. The system uses an Arduino-based control unit, LDRs (Light Dependent Resistors), a servo motor, and a solar panel. The methodology can be broken down into several key steps:

a. Light Sensing

At the core of the solar tracking system are two LDRs positioned strategically on opposite sides of the solar panel. LDRs are light-sensitive devices whose resistance decreases with increasing light intensity. These sensors are being used to detect the intensity of the sunlight drop down into the solar panel and convert it into analogy signals. The placement of the LDRs is crucial to ensure they can detect differences in light intensity, which will guide the panel to range itself optimally with the sun's position.

b. Signal Processing

The Arduino microcontroller plays a vital role in processing the data collected by the LDRs. Servo motors are most suitable for this purpose as they allow precise angular movement control. Depending on the data obtained after processing LDR, the servo motor moves the panel to position itself in alignment with the direction of the sun to ensure optimal energy harvesting throughout the day. This comparison involves subtracting one LDR reading from the other, and if the difference exceeds a predefined threshold, the system adjusts the panel's position accordingly.

c. Servo Motor Control

The Arduino sends control signals to a servo motor, which is responsible for physical rotation of the solar panel. Servo motors are ideal for this application because they provide precise control over angular movement. Based on the processed LDR data, the servo motor rotates the panel to line up with the sun's position, ensuring maximum energy capture all over the day.

d. Power Supply and Energy Storage

The solar panel, once aligned, traps sunlight and converts it into electrical energy. The energy is studied in a rechargeable battery connected to the system. The battery acts as an intermediary power source, ensuring a continuous power supply even during periods of intermittent sunlight or lowlight conditions. Proper management of energy becomes critical to keep the system efficient. Proper energy management is critical for maintaining the system's overall efficiency.

e. Integration with MHD Thruster

The energy stored in the battery is utilized to power an MHD (Magnetohydrodynamic) thruster. The MHD thruster operates by using electric and magnetic fields to accelerate a conducting fluid (like plasma) without any moving mechanical parts. The electrical energy from the battery is supplied to the MHD thruster's electrodes, generating the necessary magnetic fields and electric currents for propulsion. This integration demonstrates the practical application of the solar tracking system for powering advanced propulsion technologies.

f. Calibration and Optimization

To ensure optimal performance, the system undergoes a calibration process. The calibration process involves adjusting the sensitivity of the LDRs, setting the angles at which the servo motors can rotate, and establishing the thresholds to be used in the Arduino when processing signals. This should ensure that the solar panel is properly aligned with the sun for its maximum energy capture. In addition, a continuous monitoring of the energy flow from the solar panel to the battery and then to the MHD thruster is put in place to ensure maximum efficiency and minimize losses in energy..

IV. BLOCK DIAGRAM

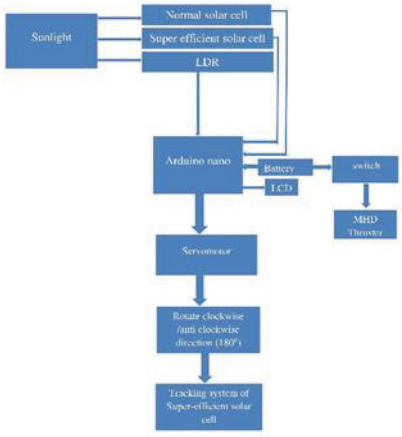

Figure 1 Block diagram

The **(Figure 1)** shows the block diagram of Magnetohydrodynamic (MHD) Thruster with Super-Efficient Solar Cell, designed to maximize energy generation and efficiently drive the thruster. The system begins with sunlight as the primary source of energy. A Light Dependent Resistor (LDR) detects the intensity and direction of sunlight, and provides input to the Arduino Uno, which serves as the primary control unit. This input allows the system to determine the ideal alignment for the solar panels to capture maximum sunlight. The control logic of the Arduino Uno drives a servo motor, that helps to adjust the position of a mini solar panel. This panel can rotate clockwise and anticlockwise up to 180°, ensuring it remains oriented toward the sunlight for optimal energy harvesting. Along with this, a normal solar panel works as a stationary energy generator, ensuring a

steady power supply. Together, these solar panels feed energy into a battery, which stores the electricity for later use, providing a consistent power supply even when sunlight is unavailable to the MHD Thruster. An LCD display is incorporated into the system to provide real-time data, showing parameters like sunlight intensity, battery charge levels, or power output. This makes the system more user friendly by enabling monitoring and troubleshooting. From the battery, power is directed through a controller to the MHD Thruster, which serves as the propulsion system. The MHD thruster uses the Lorentz Force, generated by the interaction of magnetic and electric fields, to produce thrust in a fluid medium, such as salt water. This setup ensures continuous power generation through precise positioning of the solar panels, significantly enhancing energy efficiency. By utilizing the movable solar panels, the system ensures that the MHD thruster has a reliable energy source, enabling effective and sustainable propulsion. The integration of real-time feedback through the LCD display and automated control via Arduino makes the system both efficient and innovative. In addition to its core functionality, the system offers significant potential for advancements in renewable energy utilization and propulsion technologies. The integration of a movable solar panel controlled by Arduino Uno not only maximizes energy harvesting but also demonstrates the potential of smart automation in renewable energy systems. This design can be further enhanced with advanced tracking algorithms and higher-efficiency solar cells, paving the way for future innovations. The scalability of the system also allows for customization, making it suitable for applications ranging from small boats to larger marine vessels, contributing to the development of sustainable maritime solutions.

A. PROCESS FLOW

The flowchart **(Figure 2)** indicates a system in which an Arduino uses a servo motor to move a solar panel into position for optimal sunshine exposure after contrasting the light intensity captured by two Light Dependent Resistors (LDRs). Two LDRs are used to measure light intensity, and the Arduino compares the results. The mechanism turns the panel to the left if LDR1 detects lighter than LDR2, and to the right if LDR2 detects lighter than LDR1. This assurance the solar panel is positioned optimally. Power is generated, a battery is altered, and MHD(Magnetohydrodynamic) thruster is powered by solar energy that has been captured. To optimize energy absorption, the servo motor continuously modifies the panel's position.

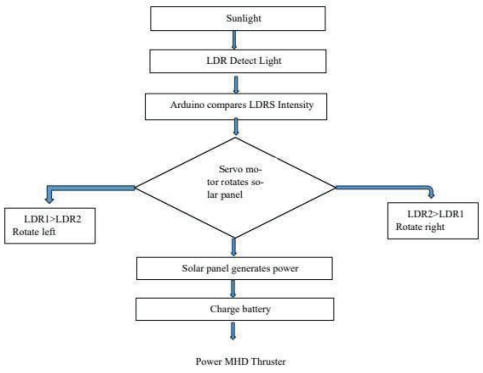

Figure 2 Flow chart

V. RESULT AND DISCUSSION

The project successfully demonstrated the feasibility of a magnetohydrodynamic (MHD) thruster powered by superefficient solar cells. In the above figures, Fig. 3. Shows the super-efficient solar cell part that is being used for the maximum utilization of the solar energy and the Fig. 4. shows the successful implementation of the MHD Thruster. Experimental results showed a significant thrust generation that propel a boat using the principle of Lorentz force. The optimized design of the MHD, incorporating high temperature superconducting magnets, resulted in maximized thrust output. The integration of high-efficiency solar cells provided a sustainable and efficient power source, enabling continuous operation in space environments and designed to maximize energy conversion from sunlight, provided the necessary power for the MHD thruster. The experimental evaluation of the Magnetohydrodynamic (MHD) Thruster with Super-Efficient Solar Cell demonstrated promising results. The thrust performance was tested in both normal water and salt water, revealing a significant difference in propulsion efficiency. The graph clearly illustrates that the thrust generated in salt water was considerably higher than in normal water.

Figure 3MHD thrust development and model boat propulsion

This increase in thrust can be attributed to the higher conductivity of salt water, which enhances the interaction between the electric and magnetic fields, thereby increasing the Lorentz force and subsequently the propulsion. In contrast, normal water, having lower conductivity, exhibited lower thrust generation due to reduced ion movement within the liquid medium.

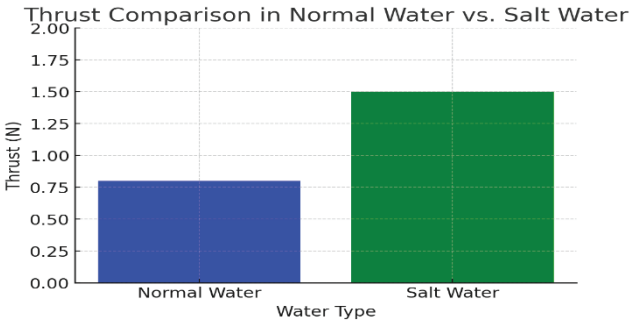

Figure 4 Thrust comparison

Additionally, the solar energy harvesting efficiency was examined by comparing a normal solar panel with a super-efficient solar cell. The results showed that the super-efficient solar cell produced a higher voltage output, which directly improved the power supply to the MHD thruster. This optimized energy conversion led to enhanced thrust performance, making it a sustainable and efficient propulsion system for both marine and space applications

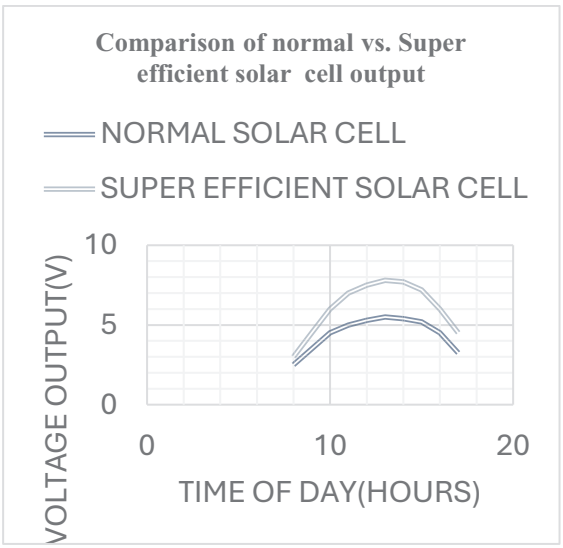

Figure 5Comparison of output voltage from both normal and super-efficient solar cells

length (in cm) and the resulting velocity (in cm/s) in a Magnetohydrodynamic (MHD) thruster system. The x-axis denotes the electrode length, while the y-axis shows the velocity of the fluid.

From the graph, it is evident that as the electrode length increases, the fluid velocity also increases. This positive correlation can be attributed to the greater effective area for current flow, which enhances the Lorentz force acting on the conductive fluid. The Lorentz force, which is responsible for the propulsion in the MHD thruster, is directly proportional to the product of the electric field and magnetic field. With longer electrodes, a greater volume of water experiences the applied electromagnetic force, resulting in higher propulsion velocity.

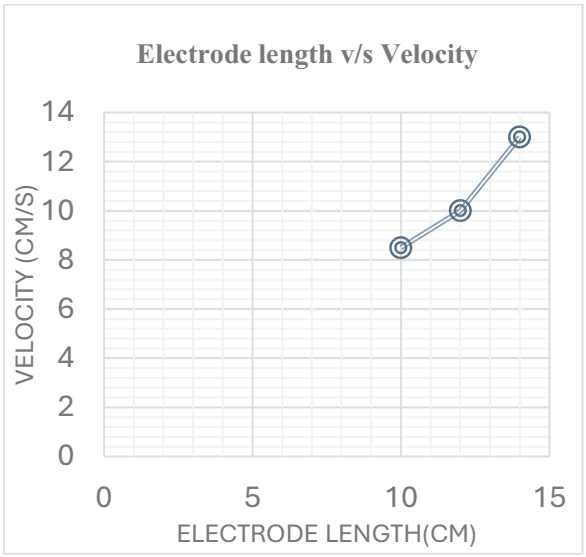

Figure 6 Electrode length versus velocity graph

Additionally, the steep increase in velocity beyond a certain electrode length indicates the nonlinear nature of the effect. While longer electrodes generally improve thrust, practical limitations such as increased electrical resistance and energy consumption may arise. Therefore, optimizing electrode length is essential for achieving efficient propulsion while maintaining energy efficiency. This experimental data supports the design choices in maximizing MHD thruster performance.

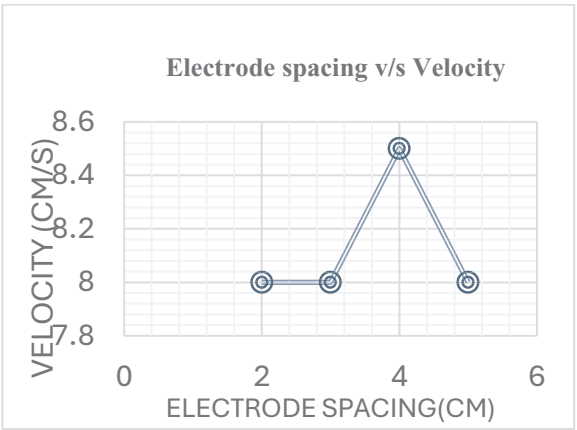

Figure 7 Electrode spacing v/s Velocity

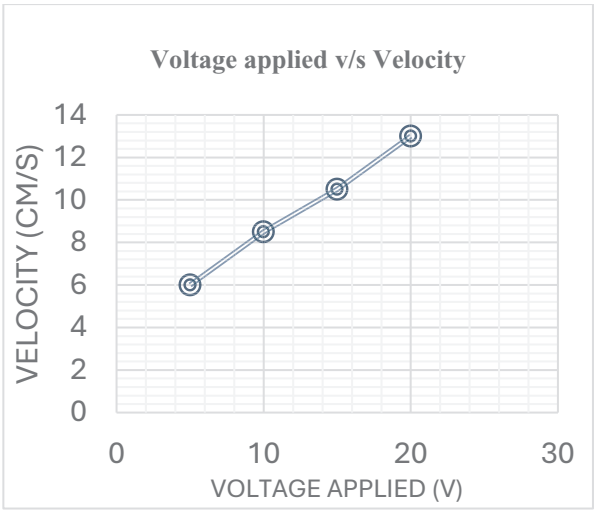

Figure 8 Voltage applied v/s Velocity

The graph represents the relationship between electrode spacing and velocity in an MHD thruster, which uses electric and magnetic fields to accelerate a conductive fluid. The x-axis denotes electrode spacing (cm), while the y-axis represents velocity (cm/s). Initially, as the electrode spacing increases, the velocity remains constant. At 4 cm, the velocity peaks, indicating optimal interaction between electric and magnetic fields, maximizing thrust

The graph illustrates the relationship between applied voltage and velocity in an MHD thruster, showing a direct correlation between the two. As the voltage increases, the velocity of the ionized fluid also rises, indicating that a stronger electric field enhances thrust. This occurs due to the Lorentz force, where the interaction of electric and magnetic fields accelerates the conductive fluid

VI. FUTURE SCOPE

The main objective of this work is to develop a super-efficient solar cell to provide maximum energy generation to the MHD thruster. The idea of batteries as a backup power source is valuable, but we would need to evaluate how efficient batteries are in a space application. Energy storage capacity, weight, and how the battery impacts the whole system would require detailed mathematical modelling and/or simulations. This is complicated and also depends on mission-specific elements; therefore, it is also considered a future work candidate.

VI. CONCLUSION

The MHD Thruster with Super-Efficient Solar Cell presents a groundbreaking step toward sustainable and efficient propulsion systems. By leveraging the principles of magnetohydrodynamics and integrating super-efficient solar cells, the system achieves high specific impulse and thrust efficiency while reducing environmental impact. This innovative design provides a dual-purpose solution for space and marine applications, offering an eco-friendly alternative to conventional propulsion systems that heavily rely on fossil fuels. The project's emphasis on harnessing renewable energy aligns with global sustainability goals, promoting green technology for future transportation solutions. The advancements in control mechanisms and real-time monitoring further enhance the system's reliability and operational precision. Looking ahead, improvements such as the incorporation of stronger magnets and a concave mirror for optimized solar tracking will significantly boost the system's overall performance and adaptability. This work not only contributes to advancing propulsion technology but also underscores the importance of renewable energy in addressing environmental challenges, paving the way for sustainable exploration and transportation across diverse domains.

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Optimal Responsive AI Cradle for Little Explorers (O.R.A.C.L.E)

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***Abstract*—The objective of this smart baby cradle is to provide a multifunctional, high-tech solution that enhances both the comfort and safety of the baby while offering convenience to parents. The cradle will feature an integrated system that plays soothing songs or lullabies to help the baby sleep and respond to the baby's cries. Additionally, the cradle will include attached toys to engage and entertain the child. The motion of the cradle will be controlled automatically, and the fan speed will also be adjusted automatically. A contactless sensor in the cradle will monitor the room's temperature and adjust the fan speed accordingly, ensuring the baby's environment remains comfortable. To enhance safety, the baby will be monitored through an ESP32 cam. If an unsafe position is detected, a notification will be sent to the parents or caretakers via Telegram. If no response is received, a built-in buzzer will activate as an additional alert. Furthermore, the cradle will include a wetness detection system, which will notify parents if wetness is detected. The baby's crying will also be detected through the ESP32 cam and sound sensor, with a notification sent to parents via Telegram if cry will also be detected. And as a innovation eye monitoring of the baby for sleep pattern analysis, health monitoring etc. is also done.This integrated system aims to provide peace of mind, enabling parents to monitor and care for their baby from anywhere with ease.**

Keywords*—Baby Monitoring, Cry Detection, Sound Sensor, Contactless Sensor, Temperature Monitoring, Fan Speed Control, Wetness Detection, Parent Notification System.

I. Introduction

The Smart Cradle System is an comprehensive and innovative solution designed to address the fundamental needs of babies and their caregivers by providing a high-tech, automated monitoring system. In this fast-paced world of modern parenting, the need for an intelligent, efficient, and reliable system to ensure the baby's safety, comfort, and well-being is more crucial than ever. The Smart Cradle System integrates sensors, actuators and smart technology to offer continuous real-time monitoring of baby's, which enables parents to stay informed and responsive to their baby's needs—without being physically present at all times.

This cradle is equipped with various sensors like sound sensor, moisture sensor, and temperature sensor and these sensors tracks baby's position, crying, wetness and temperature and as a output it in turn gives notification to the parents or caretakers through telegram or adjust the temperature of the fan fixed to it. If the parent or caretaker doesn't respond within a designated timeframe, an alarm buzzer activates to further ensure the baby's safety.

Beyond basic safety, the Smart Cradle System is designed to foster the baby's emotional and physical well-being. The cradle comes with soothing features, such as calming music and interactive toys, that engage and relax the baby, promoting a peaceful atmosphere. These features help reduce anxiety or fussiness and can significantly improve the baby's sleep quality by providing gentle distractions and comforting stimuli. This integration of entertainment and comfort mechanisms not only helps the baby feel safe but also supports developmental milestones by introducing sensory stimulation through sounds and toys.

The Smart Cradle System ensures a baby's safety, comfort, and hygiene through advanced monitoring features. It includes a wetness detection sensor that alerts caregivers when a diaper change is needed, maintaining cleanliness and preventing discomfort. The system also features temperature sensors that regulate airflow and control fan speed automatically, ensuring an optimal environment. With movement tracking, emotional monitoring, and environmental controls, this cradle offers comprehensive care, giving parents peace of mind and greater convenience in managing their baby's well-being.

II. Literature review

Recent advancements in smart healthcare have led to the development of innovative monitoring systems for infants and elderly patients. A Bluetooth-enabled device was designed to detect wetness and bleeding, aiding caregivers by using fine-wire sensors in diapers or bandages [1]. When moisture is detected, an alarm is triggered and sent via Bluetooth to a smartphone or computer, ensuring timely

intervention. However, this system is limited to detecting wetness and does not provide broader monitoring features.

In contrast, the IoT-based Baby Monitoring System (IoT-BBMS) offers a more comprehensive solution by tracking multiple parameters, including temperature, moisture, and crying [2]. Unlike the Bluetooth-based device [1], this system transmits data via Wi-Fi to a server, allowing remote access to video feeds and control over an automatic rocking cradle and lullabies. While more advanced, IoT-BBMS requires an internet connection, which may limit its usability in certain environments.

Furthermore, an emotion recognition system expands on infant monitoring by analyzing facial expressions and vocal cues to classify emotions [3]. Unlike [1] and [2], which focus on physical well-being, this system provides emotional insights using AI-based classification, achieving 85.3% accuracy. Combining these approaches could lead to a more holistic infant monitoring solution.

III. Block Diagram

We represent a innovative and cost effective system for monitoring the baby through telegram even staying in another room.

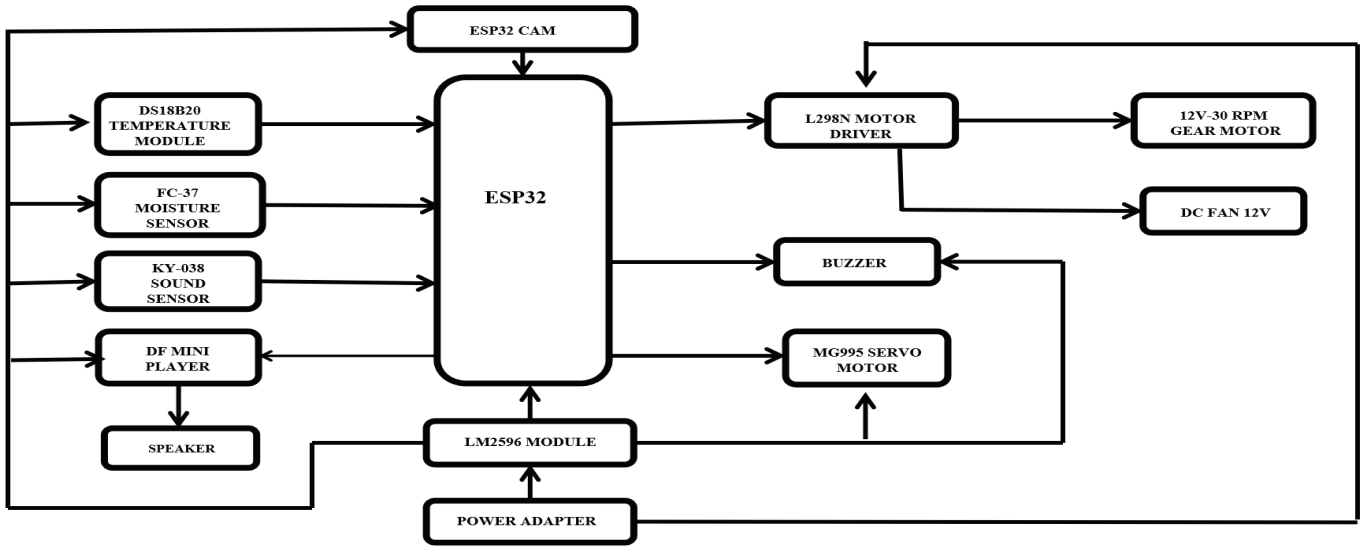

Fig. 1. Block diagram.

This block diagram illustrates a smart automation and monitoring system centered around the **ESP32** microcontroller. The ESP32 serves as the brain of the system, interfacing with multiple input sensors and output components to enable real-time data collection, processing, and control. Various sensors are connected to the ESP32, allowing it to monitor environmental conditions and respond accordingly.

The DS18B20 temperature module is used to measure ambient temperature, which is being used for temperature-based automation. Similarly, the FC-37 moisture sensor detects moisture levels in the cradle. Another important input component is the KY-038 sound sensor, which captures sound levels and can trigger specific actions based on noise intensity. Additionally, the system includes an ESP32 CAM module, which allows it to capture images or video. This feature is being used to monitor the face emotions of baby .The ESP32 processes sensor inputs and determines the appropriate response by activating various output components.

For motion and mechanical control, the system incorporates an L298N motor driver, which enables the operation of a 12V-30 RPM gear motor and a 12V DC fan. These motors can be used for various purposes, such as ventilation, automation of moving components, or robotics applications. Furthermore, an MG995 servo motor is included for precise angular movements and positioning systems.

The system also integrates a buzzer to provide audible alerts, which can be used for security alarms, process notifications, or emergency alerts. Additionally, a DF Mini Player MP3 module connected to a speaker allows the system to play pre-recorded lullaby, which makes baby comfortable.

Powering the system efficiently is crucial, and this is managed by an LM2596 voltage regulator module, which ensures stable voltage supply from a power adapter to all components. This ensures the smooth operation of the ESP32 and connected modules without power fluctuations.

The combination of sensors, motors, audio feedback, and camera functionalities makes it a versatile and powerful solution for monitoring of baby for parents or caretakers.

IV. Hardware Components

This project utilizes a combination of sensors, actuators, and communication modules, with the ESP32 as the central controller. Key components include the DS18B20 temperature sensor, FC-37 moisture sensor, KY-038 sound sensor, and the ESP32 Cam for environmental monitoring and interaction. Additional hardware such as the L298N motor driver, MG995 servo motor, DF Mini Player, and DC fan provide control and multimedia features to enhance the system's functionality.

A. ESP32

The ESP32, created by Espressif Systems, is an affordable and energy-efficient system-on-chip (SoC). It is equipped with a dual-core or single-core Tensilica Xtensa LX6 processor and built-in Wi-Fi and Bluetooth (including BLE), making it a great choice for Internet of Things (IoT) projects.

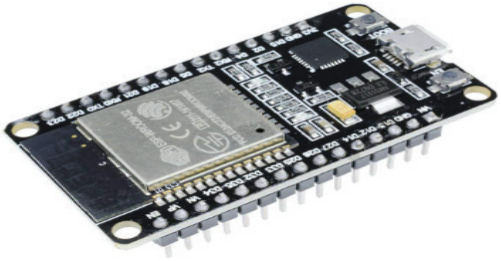

Fig. 2. ESP32

Specifications

- Processor: Dual-core/Single-core Xtensa LX6 (up to 240 MHz)
- Connectivity: Wi-Fi (802.11 b/g/n), Bluetooth 4.2 (Classic & BLE)
- Memory: SRAM, Flash Storage
- GPIOs: Multiple digital and analog pins
- Peripherals: SPI, I2C, UART, ADC, DAC, PWM
- Low Power: Supports deep sleep mode for power efficiency

B. ESP32 CAM

The ESP32-CAM is a cost effective development board featuring an ESP32 SoC with a built-in OV2640 camera. It supports Wi-Fi, Bluetooth, and microSD storage, making it ideal for IoT and surveillance applications. With a dual-core processor (240 MHz), GPIOs, UART, and PWM, it enables face recognition, object detection, and smart security systems. Lacking a USB-to-serial converter, it requires an FTDI adapter for programming. Compact and affordable, it's perfect for AI-driven image processing projects.

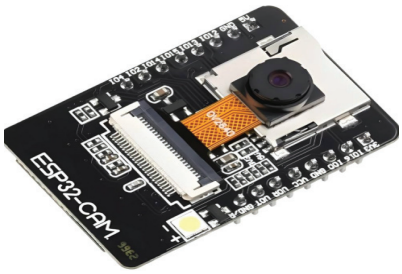

Fig. 3. ESP Cam

C. DS18B20 Temperature Module

The DS18B20 is a temperature sensor that provides readings from -55°C to +125°C with ±0.5°C accuracy. It communicates using the 1-Wire protocol, requiring only one data line for multiple sensors. Operating at 3.0V–5.5V, it supports parasitic power mode. With a waterproof variant, it's ideal for industrial, weather monitoring, and IoT applications. Its compact size, high precision, and ease of integration make it perfect for embedded systems and Arduino projects.

Fig. 4. Temperature Sensor

D. FC-37 Moisture Sensor

The FC-37 is a soil moisture sensor that detects water content using two probes to measure resistance. It operates on 3.3V–5V and provides both analog and digital outputs for easy interfacing with Arduino and microcontrollers. The sensor includes a comparator (LM393) for adjustable sensitivity. It is widely used in automatic irrigation, smart gardening, and IoT agriculture. Here in this system it is being used for detecting wetness in baby.

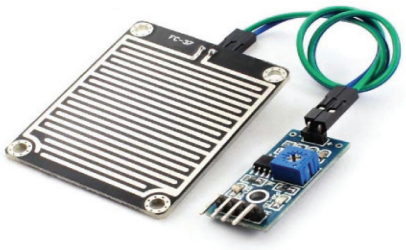

Fig. 5. Moisture Sensor

E. KY-038 Sound Sensor

The KY-038 is a sound sensor module that detects audio signals using a condenser microphone and an LM393 comparator. It operates on 3.3V–5V and provides both analog and digital outputs for interfacing with Arduino and microcontrollers. The sensitivity is adjustable via a potentiometer, making it ideal for sound-activated systems, voice detection, and security applications. Widely used in IoT and automation, it enables projects like clap-controlled devices and noise monitoring systems.

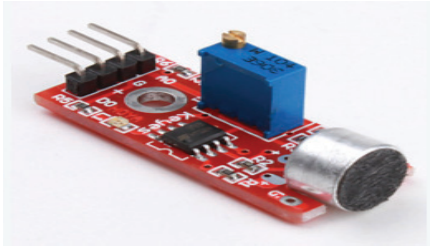

Fig. 6. Sound Sensor

F. Servo Motor

A servo motor is a used for positioning and speed control. It operates on PWM signals to set angles (0°–180° for standard servos) and works with 5V power in hobby applications. Commonly used in robotics, automation, and RC vehicles, it consists of a DC motor, gears, and a feedback system for accurate movement. Servo motors are essential for robot arms, camera gimbals, and smart systems, offering high torque and stability.

Fig. 7. Servo Motor

IV. Results and Conclusion

The Smart Baby Cradle, powered by ESP32, integrates multiple sensors and actuators to ensure a safe, comfortable, and convenient environment for infants while assisting parents in remote monitoring. The ESP32 acts as the central controller, processing data from various sensors and automating responses. The DS18B20 temperature sensor detects room temperature, allowing ESP32 to adjust the fan speed for a comfortable environment. The KY-038 sound sensor detects the baby's cries, prompting ESP32 to trigger the DF Mini Player for lullabies and send alerts via Telegram. The ESP32-CAM enables real-time video monitoring, ensuring continuous supervision. If the baby is in an unsafe position, ESP32 activates a buzzer alert and sends notifications. The FC-37 moisture sensor, interfaced with ESP32, detects wet diapers, notifying caregivers for immediate action. The MG995 servo motor, controlled by ESP32, automatically rocks the cradle when required, soothing the baby.

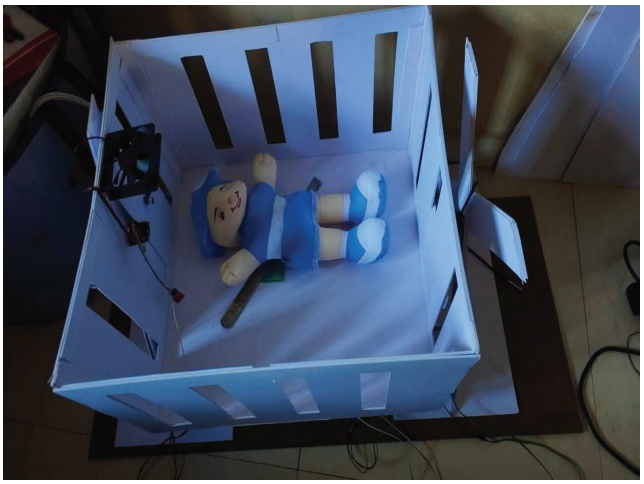

Fig. 8. Prototype of cradle

Fig. 9. Notification received on Telegram while the baby was crying.

During testing, the system demonstrated efficient real-time responses to environmental changes. However, challenges such as network dependency for real-time alerts and sensor sensitivity adjustments were encountered. These were resolved through sensor calibration and optimized placement. The system can be further enhanced by incorporating a rechargeable backup power supply, improved sound detection algorithms, and better response accuracy. Overall, the ESP32-based Smart Baby Cradle provides a modern and reliable solution for childcare, ensuring the baby remains safe and comfortable while significantly reducing parental stress through automated monitoring and smart alerts.

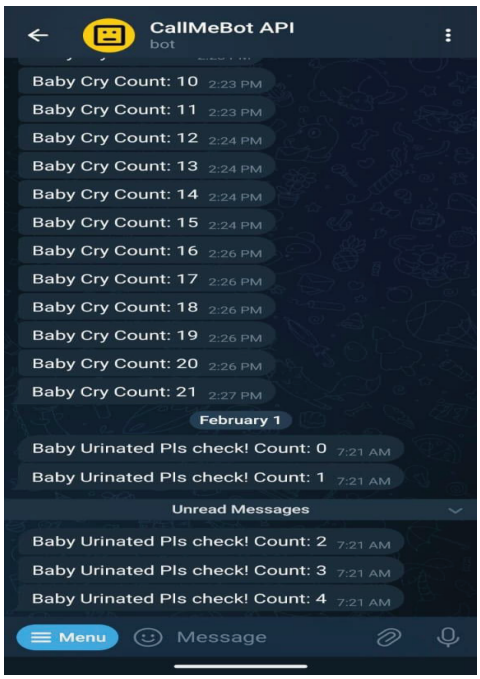

Fig. 10. Notification received on Telegram while the baby was crying.

V. Conclusion

The ESP32-based Smart Baby Cradle successfully integrates multiple sensors and automation features to provide a safe, comfortable, and convenient environment for infants. By utilizing ESP32 as the central controller, the system ensures efficient monitoring and automatic responses based on temperature, moisture, and sound detection. The DS18B20 temperature sensor helps regulate fan speed, maintaining an optimal environment, while the KY-038 sound sensor detects the baby's cries, triggering soothing lullabies via the DF Mini Player and sending real-time alerts through Telegram. The ESP32-CAM provides continuous monitoring, ensuring parents can check on their baby remotely. If an unsafe position is detected, the buzzer alert system is activated, enhancing safety. Additionally, the FC-37 moisture sensor detects wet diapers, and the MG995 servo motor enables automatic rocking for soothing the baby.

Throughout testing, the system demonstrated reliable and accurate responses to environmental changes. However, challenges such as network dependency and sensor sensitivity tuning were addressed through calibration and optimized placement. Future improvements could include battery backup, improved sound recognition, and enhanced system stability. Overall, the Smart Baby Cradle provides a modern childcare solution, allowing parents to monitor their baby with ease while ensuring a safe and nurturing environment.

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Aquabot: Floating waste collections and seggregation robot

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***Abstract*—The aquabot is intended to automate the process of water body cleaning through the collection and segregation of waste into organic and non-organic types. Floating waste pollution of water has become a serious environmental issue, impacting marine life and water quality degradation. This project proposes to solve this problem using an autonomous system capable of effectively traveling across water surfaces, gathering garbage, and sorting it according to classification outcomes. The robot utilizes an ESP32-CAM to take pictures of gathered trash, which are analyzed by Edge Impulse to decide whether the trash is organic or not. The NodeMCU microcontroller serves as the controller, controlling the motor movements and waste collection. A conveyor system provides smooth collection, and a servo motor-operated segregation unit sends waste into separate compartments. The system is powered by a 12V rechargeable battery and a step-down module for voltage regulation across various components. By using an independent method of managing waste in water bodies, the project minimizes the use of labor, increases efficiency, and ensures a cleaner aquatic environment.**

***Keywords*—Floating waste collection, Autonomous system, Segregation robot, Waste classification ,ESP32-cam, NodeMCU**

I. Introduction

Water pollution is an emerging issue resulting from human actions, and there is a resultant upsurge in floating trash like plastic bags, food packaging, and vegetative material. The pollution not only disfigures water bodies but also poses a severe risk to aquatic life by polluting water bodies and harming sea life. Current waste collection practices entail manual processes, which are labor-intensive, ineffective, and too cumbersome for industrial application. Further, inefficient segregation of waste post-collection complicates processing and recycling the materials. In an attempt to overcome this limitation, the project presents a self-governing floating waste collection and segregation robot that is efficient at collecting and separating the waste into organic and inorganic categories.The design floats on water and can operate without any manual intervention. ESP32-CAM module is utilized for capturing images of the gathered trash, which are later processed by Edge Impulse for segregating the trash on the basis of its characteristics. NodeMCU microcontroller handles the waste collection and movement of the robot. The efficient pickup of waste is provided with a motor-based conveyor system, while the classified trash is fed into distinct sections by a servo motor-based segregation system. The whole system is driven by a 12V rechargeable battery, supplemented by a step-down module for delivering the needed voltage to various components. With the combination of hardware and software components, the project offers an efficient and real-world solution to automated waste collection and management of water bodies and, in the long run, environmental sustainability.

II. Literature Survey

AquaBot – Water bodies cleaning and monitoring bot, an automated system for waste collection utilizing a conveyor belt that effectively picks up floating trash from the water surface and delivers it to a storage tank. At the front, there is the continuously rotating conveyor belt where only solid waste is gathered and excess water filtered out. At the top, the storage tank, being placed for maximum stability, receives the accumulated trash, while the level is constantly monitored by an ultrasonic sensor. Notifications are sent at 75% capacity for prompt disposal, and collection is stopped at 90% to avoid overflow. This system facilitates smooth waste disposal, reducing manual intervention while ensuring regulated waste management in water bodies.[1]

Automatic Waste Segregator system applies image classification to effectively sort waste into dry, wet, and plastic categories. A camera takes pictures of waste, and a

machine learning algorithm processes them to identify the category [2]. The efficiency of garbage removal from water bodies is improved by the waste identification and removal system that uses image processing. A PiNoIR camera is used to process images in order to detect the floating trash. The trash is picked up by a robotic arm and dumped into an on-board storage cylinder when it is identified. When the storage is full, the boat utilizes GPS to go to a predetermined dumping spot based on an infrared sensor that measures the amount of waste. By reducing human operations and enabling accurate waste identification and mechanized collection, this technology improves the overall efficiency of garbage collection in water bodies. [3].

III. Proposed Architecture

Block diagram of the aquabot is shown in Fig 1.

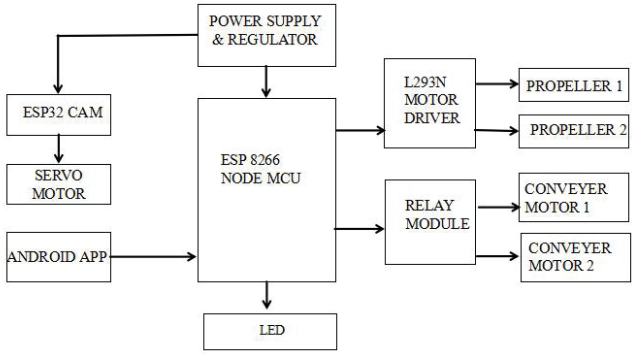

Fig 1. The Block diagram

The waste collection and segregation robot that floats works in various stages, including waste collection, image processing to classify, and segregation according to the classified category. The robot's mechanical system includes a floating platform with a conveyor belt mechanism for collecting the waste from the water surface. The gear motors power the motion of the conveyor belt to have a continuous supply of waste to the collection point. When waste is gathered, the ESP32-CAM module takes photos of the incoming waste, which are processed with Edge Impulse to decide if the waste is organic or non-organic. Classification depends on a machine learning model that has been trained, and this model checks the characteristics of the waste and labels it with the correct category.

After the waste categorization is done, the ESP32 cam turns on the servo motor-driven segregation process. The segregation process involves a sliding flap or divider that directs the waste to one of two defined compartments—the one for organic waste and the other for inorganic waste. The whole system is driven by a 12V rechargeable battery, which feeds the motors, microcontroller, and camera module. Voltage is controlled through a step-down module (XL4015) to ensure that components receive the correct power levels without overloading. For mobility and direction, the robot has gear motors (60 RPM and 30 RPM, 12V) that guide it over the water surface. They allow the robot to position itself as necessary for more effective gathering of the wastes. The entire system is energized and managed by a large rocker switch with ease. After the process of waste collection is finished, the waste compartments can be emptied manually or an automated disposal system can be incorporated in future upgrades. Through the use of this autonomous waste collection and segregation system, the project hopes to reduce water pollution, decrease human labor, and encourage sustainable waste management practices in lakes, ponds, and other bodies of water.

IV. Hardware Components

A. NodeMCU (ESP8266)

The NodeMCU (ESP8266) is an open-source ESP8266EX Wi-Fi SoC-based development board that comes with a 32-bit Tensilica Xtensa LX106 processor clocked at 80 MHz, with a possibility of overclocking to 160 MHz. It comes with 4 MB of flash, 64 KB of SRAM, and is Wi-Fi standard 802.11 b/g/n (2.4 GHz) having Station (STA), Access Point (AP), and dual-mode support. The board runs at 3.3V with an input voltage of 4.5V to 9V via the Vin pin and has an average operating current of 70 mA, with a deep sleep current of below 20 µA. It provides 17 multifunctional GPIO pins, a single 10-bit ADC pin, and supports SPI, I2C, and UART communication protocols. Key features are an integrated CP2102 or CH340 USB-to-serial port for simple programming, a built-in antenna for good wireless connectivity, and voltage regulation with AMS1117-3.3V. The board has reset and flash buttons, and power and GPIO status LEDs. Its small size is 49 mm in length, 25 mm in width, and 13 mm in height (with pin headers), and has an estimated weight of 8.5 g.

Fig 2. NodeMCU (ESP8266)

B. ESP32-Cam

The ESP32-CAM is a small camera module using the ESP32-S microcontroller, a 2MP OV2640 camera sensor to capture images. It has a dual-core Tensilica LX6 CPU operating at 240 MHz, 520 KB SRAM, and 4 MB external PSRAM for processing images. Wi-Fi 802.11 b/g/n and

Bluetooth 4.2 enable it to support wireless communication stably. It consists of 9 GPIO pins that support UART, SPI, I2C, and PWM with a single 10-bit ADC pin. It runs from 3.3V to 5V with a draw of approximately 180 mA on transmit. There are also extra features such as a built-in SD card reader to store images, a PCB antenna for Wi-Fi connectivity, and a reset switch. Its small size is 27 mm x 40.5 mm, which makes it ideal for embedded systems such as waste classification in the robot with Edge Impulse.

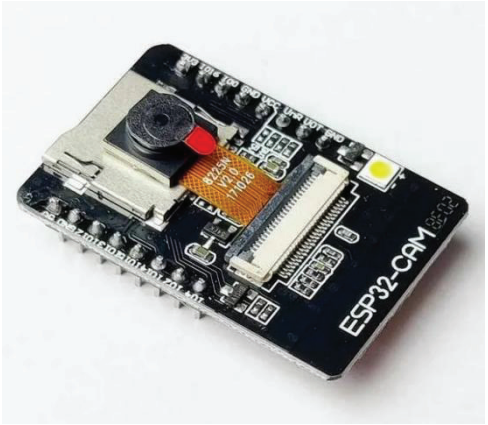

Fig 3. *ESP32-Cam*

C.L298N Motor Driver

L298N Motor Driver is a dual H-Bridge motor driver integrated circuit that may be used to operate two DC motors in both directions. It can generate a maximum output current of up to 2A per channel and operate in the voltage range of 5V to 35V. To power low-voltage components, the module has an internal 5V regulator and back EMF protection diodes for an external power source. It has two enabling pins (ENA, ENB) for PWM speed control and four input pins (IN1, IN2, IN3, IN4) for motor direction control. To guarantee smooth motion, the NodeMCU instructs the L298N to control the motors' speed and direction. It has heatsinks for effective thermal management and is generally 43 mm x 43 mm x 27 mm in size.

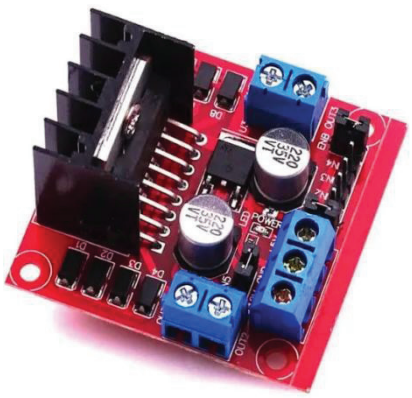

Fig 4. L298N Motor Driver

C. XL4015 Step-Down Module

The XL4015 Step-Down Module is a DC-DC buck converter capable of regulating and stepping down voltage from a higher input, i.e., a 12V battery, to a reliable lower voltage compatible with other components like the NodeMCU and ESP32-CAM. It has an operating input voltage range of 4V to 38V and delivers an adjustable output voltage of 1.25V to 36V with a maximum output current of 5A. With a high conversion efficiency of 96%, the module minimizes energy loss. It also has built-in thermal shutdown, short-circuit protection, and current limiting for safe operation. The onboard potentiometer provides easy voltage adjustment, and the large heatsink provides efficient heat dissipation. Small in size, the module is about 54 mm x 23 mm x 15 mm, making it perfect to be integrated into the power management system of the robot.

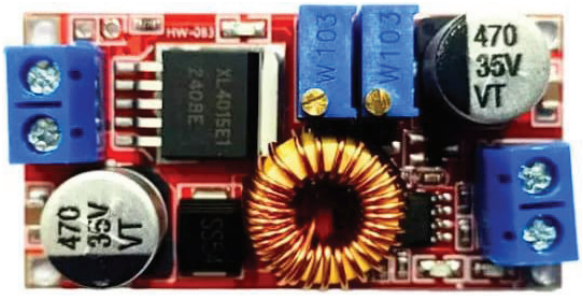

Fig 5. *XL4015 Step-Down Module*

V. Circuit Diagram

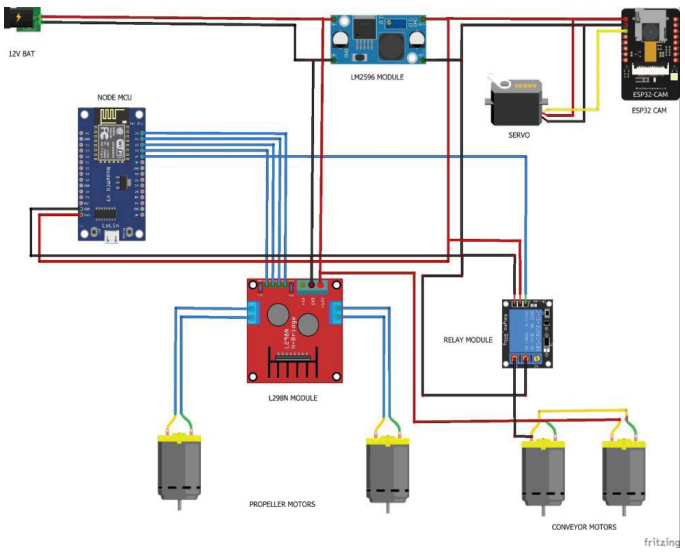

Fig 6. Circuit diagram

The circuit layout includes a 12V battery as the main power source, supplying power to different components via an

LM2596 step-down module. As different components have different voltages, the LM2596 module is utilized to step down 12V to 5V to supply power to the NodeMCU, ESP32-CAM, servo motor, and relay module. The NodeMCU, the main controller, is supplied power from the 5V output of the LM2596 module, while the
CAM is also associated with this controlled power. The L298N motor driver controls the movement of the robot by controlling the propeller motors. The L298N inputs are linked with the GPIO pins of the NodeMCU so that it can send control commands to adjust the speed and direction of the motors. The 12V from the battery is also fed directly into the motor driver to provide enough power for the motors.
The ESP32-CAM takes the pictures of the waste gathered and transmit them for processing and classification using Edge Impulse. The results of the classification assist in waste segregation by regulating the movement of a servo motor, which guides waste into respective compartments depending on whether it is organic or non-organic. The servo motor is controlled by the ESP32 cam and powered by the 5V output of the LM2596 module. The circuit also incorporates a relay module to switch the conveyor motors on and off. The relay is controlled by the NodeMCU, which dictates when the conveyor system needs to be turned on to lift and move waste into the collection zone.
The propeller motors, which power the movement of the robot over water, are connected to the output pins of the L298N motor driver to individually control each motor in terms of directional movement. The conveyor motors, used for conveying gathered trash, are energized using the relay module, where they work only when needed. The whole system is coordinated together, with the NodeMCU as the main processing unit, governing movement, waste collection, and ESP 32 cam coordinates image processing, and segregation. Through efficient management of power supply, motor control, and image processing, the circuit makes the robot able to operate independently in collecting and sorting floating waste.

V. RESULTS AND DISCUSSION

Fig 7. Aquabot

The Aquabot effectively harvests and separates floating trash with the ESP32-CAM for image capture and Edge Impulse for classification. The NodeMCU controls it, moving smoothly with the L298N motor driver, while the XL4015 step-down module provides a stable power supply. The MG90 servo motor facilitates efficient waste separation. With secure wireless communication for remote monitoring, the Aquabot shows practical application in waste management. A picture of the finished project is provided below, demonstrating its design and operation.

VII. CONCLUSION

Floating trash segregation and collection robot is an innovation technology aimed at tackling the developing problem of water pollution through effective collection and segregation of waste. Using hardware components such as NodeMCU, ESP32-CAM, servo motors, and conveyor belt, and processing the data using Edge Impulse, the robot recognizes and divides the garbage into organic and non-organic waste. Convenient travel across bodies of water is made possible by the propeller system, and efficient waste disposal is guaranteed by the conveyor and servo-controlled segregation system. The system is effective and sustainable because of the circuit design, which guarantees optimal power management, seamless component communication, and automatic operation. In addition to cleaning the waterways, this initiative shows the potential of IoT and AI-based robots for environmental preservation and opens up new directions for the advancement of automated waste management technology.

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Portable AI-Driven Stress Detection and Relief Assistant

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***Abstract*—A handheld AI-powered voice assistant has been created to detect and manage stress in real time. It is built on a Raspberry Pi with a camera and biometric sensors integrated in order to monitor heart rate, SPO, and body temperature. Stress is measured based on facial expression analysis through a Convolutional Neural Network (CNN), combined with biometric feed for improved accuracy. Based on the data gathered, the system calculates a stress score and gives personalized recommendations, such as relaxation techniques or medical recommendations. User privacy is preserved, with encrypted data storage and consent-based collection. Extensive testing in controlled and real-world settings provides reliability and continued improvement. With a voice-guided interface, the product is easy to use and accessible to all ages. Its lightweight and compact nature makes it portable, offering a convenient and proactive means of stress management at any time, anywhere.**

I. Introduction

Stress has also become an inexorable part of day-to-day living, immensely contributing to both physical and psychological wellbeing. Ongoing stress contributes to anxiety, fatigue, as well as full-fledged disease conditions, highlighting the need for its early diagnosis and control. Existing stress measuring strategies tend to depend on clinical assessment, and often this will be inconvenient and out of reach at times. This has prompted an AI-enabled real-time system to monitor stress via biometric sensors, face detection, and machine learning protocols. The system is based on a Raspberry Pi, which acts as the processing unit, combining the inputs from several sensors. A temperature sensor, a SpO2 sensor and a heart rate sensor continuously monitor physiological responses associated with stress. Apart from biometrics, facial expressions are analyzed by a Convolutional Neural Network (CNN) facial recognition model to identify stress features. By integrating all these inputs, the system produces a stress score, giving an even better snapshot of the emotional and physiological well-being of the user. The moment stress is detected, the device provides individualized interventions like breathing exercises, relaxation, or even listening to soothing music. The system is provided with a voice-guided interface, making it simple for all ages to utilize. Also, privacy and security of data is given importance to ensure that data from the users is encrypted and processed safely Portable in nature, this is a simple and handy machine learning-based stress monitoring gadget that can help one monitor his/her stress at any time and from any location. Having real-time monitoring with machine learning, this system provides an advanced way of managing stress, pushing overall wellness and mental well-being.

II. Block Diagram of Portable AI Based Voice Assistant for Stress Level Monitoring

The block diagram illustrates a real-time stress monitoring system using facial recognition, biometric sensors, and Raspberry Pi to quantify the stress levels and recommend customized cures. The system collects physiological data from a temperature sensor, heart rate sensor, and SPO sensor, which help identify stress markers from body variations. The system also monitors facial expressions for signs of stress using a Convolutional Neural Network (CNN)-based face recognition system. These inputs are input to a Raspberry Pi, which generates a stress score using machine learning algorithms. Based on the level of stress, the product offers personalized cures, i.e., guided breathing exercises, listening to soothing music, or offering professional advice. The voice interaction makes it accessible to all, and hence a small, portable, and useful tool to control stress. The system also integrates real-time feedback, allowing continuous monitoring and adjustments based on the user's stress levels. The machine learning model adapts over time, improving its accuracy in recognizing stress patterns and recommending effective solutions. Additionally, the system can store historical stress data, enabling trend analysis and long-term health insights. Its compact design and low power

consumption make it ideal for personal and professional use, offering a user-friendly interface through both visual and voice guidance.

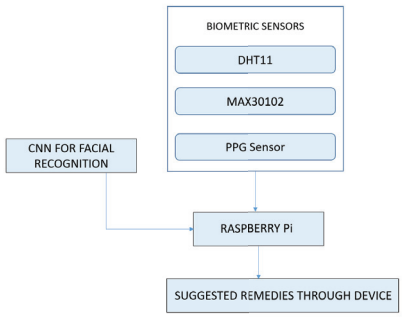

Fig. 1. Block Diagram

III. METHODOLOGY

The software part includes Pre-processing of image, Training of Convolutional Neural Network, Facial Recognition and Image Acquisition

A. Pre-processing of image

The initial step is preprocessing of images when techniques such as scaling, normalization, and data augmentation are utilized to make the model more accurate and general. The Adam optimizer is applied subsequently to train the model following a well-formatted CNN, designed to capture key spatial features. There are multiple methods used to measure its performance, and visualizations are created in order to track trends in accuracy and loss, which provide insight into how well the model learns and improves with time.

1.Organizing Data: The data were structured into several files, every one of them being a separate emotion, for example, ”happy” or ”angry.” This approachable organization eased the process of linking photos with their respective labels while loading data.

2.Loading and Colour Formatting: The images were loaded with the OpenCV library (cv2.imread) and were converted to RGB mode to ensure uniformity in color scheme throughout the dataset. This ensured smooth compatibility with different machine learning platforms. Each class was also given a distinct numerical label to enable smooth processing by the model.

3.Image Resizing and Normalization: The original dimensions of the images were different, so all of them were resized to 50 × 50 pixels to ensure consistency in input sizes. Two advantages of standardizing image sizes were reducing computational complexity and ensuring the compatibility of the dataset with the CNN model, which accepts fixed input sizes.

4.Pixel Value Scaling: Pixel values, which were initially between 0 and 255, were normalized to lie within the interval [0, 1] by dividing each value by 255. This was done to maintain numerical stability during training since it avoided large gradients and made the overall optimization process more efficient.

5. Splitting Data: The data was split into two primary segments: the training set, which represented 80% of the data, and the testing set, which contained the other 20%. The training set was utilized to allow the CNN to learn and identify unique features that belonged to each category so that the model would be well-trained with varied data. Concurrently, the test set was used to analyze the model’s performance on unseen images and gain insight into its ability to generalize. Balanced class distribution in both subsets was ensured by performing stratified sampling, where the proportion of every category remained the same throughout the dataset.

6.Augmentation for Diversity: To diversify the training set and enable the model to generalize better, a few data augmentation techniques were utilized. Flipping was utilized to create alternative views so that the model could identify objects from various orientations. Small-angle rotations were implemented to simulate minimal positional changes, making the model robust to orientation variations. Scaling was also applied to vary image sizes, simulating varying distances of viewing. These improvements not only diversified the dataset but also enhanced the model’s capacity to learn and perform well when it is faced with new, unseen images.

B. Training of Convolutional Neural Network

1.Convolutional Layers: Three convolutional layers with ReLU (Rectified Linear Unit) activation were used to identify essential patterns in the input images, such as edges, textures, and shapes. These patterns formed the basis for higher-level feature extraction.

2.Model Compilation and Training: Following every convolutional layer, max-pooling was also used to down sample the feature maps, i.e., scale them down with a loss in spatial details that was not really significant. Down sampling was helpful in reducing the computational costs at the same time as maintaining relevant features that helped in correct identification. Max-pooling further helped in generating translational invariance to ensure that even if objects on the images took up slightly differing positions, the model would be effective. In order to mitigate the threat of overfitting, a dropout layer with 25% was introduced. The process of this technique involved disabling randomly a portion of the neurons in training so that the model was forced to learn more varied features instead of heavily relying on individual patterns. Thus, the model acquired a greater capacity to generalize to new data. After the feature extraction, fully connected layers with the use of ReLU (Rectified Linear Unit) activation were applied. These layers converted the extracted features into a better structured and more meaningful representation in order to enhance the model’s capacity to differentiate between various categories. Lastly, the network finished with an output layer using a softmax activation function. The final step transformed the processed data into probability scores to allow the model to

classify images into one of the five emotion categories defined beforehand.

3.Loss Function and Optimization Strategy: The model employed the sparse categorical cross-entropy loss function to quantify the disparity between the predicted and actual labels, thus being perfectly suited for multi-class classification tasks. The loss function assisted the model to learn the differences between categories well by inflicting penalties on incorrect predictions.For the realization of effective and stable learning, the Adam optimizer was used. The optimization method was responsible for dynamically scaling down the learning rate during training. Through adjusting the learning rate from the gradients, Adam enabled the model to converge better, thus enhancing its potential to achieve maximum performance without falling into problems of slow learning or being trapped in suboptimal solutions.

4.Training Configuration: The training procedure was formulated to strike a balance between performance and efficiency. It was performed in mini-batches of 32 images, which offered a good compromise between the use of computational resources and model stability during updates. The model was trained for 5 complete epochs, with sufficient iterations for the network to learn patterns and features within the dataset effectively. In order to enable the model's generalizability to unseen data, 20% of training data was reserved as a validation set.

5. Model Evaluation and Performance Analysis: To assess the performance of the model after training, a number of metrics were utilized to provide an all-around measurement. Accuracy counted the percentage of images correctly identified, giving an overall measure of the success of the model. A confusion matrix was used to examine the pattern of correct and incorrect predictions by all classes to provide insights into particular strengths and weaknesses. Further, sensitivity and specificity were computed in order to gauge the model's performance in distinguishing true positives and true negatives, respectively. A classification report in detail was also generated, noting precision, recall, and F1-scores for all emotion categories, which can be used to better understand the performance of the model. In order to save and utilize the model, it was stored in different formats such as JSON (JavaScript Object Notation) HDF5 (Hierarchical Data Format 5) and the complete model structure to allow for flexibility and compatibility across platforms. The trained model was applied to unseen data to assess real-world usability. For further study of the training process, graphs of performance were created to present trends in loss and accuracy throughout epochs. These visualizations offered useful insights into the learning behavior of the model, highlighting its strengths and where it could be improved.

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C. Facial Recognition and Image Acquisition

The procedure is started with OpenCV and a webcam-based face detection in real-time. For detection of the human face from the video frame, the system uses the Haar Cascade classifier (Pre-trained model) . A set of fixed frames are grabbed by the system (50 frames in our scenario) in order to collect several samples for stress assessment. Frames are horizontally flipped for homogeneity and transformed to grayscale format to improve face feature detection quality. Detected faces are boxed so that extraction of useful facial features for further processing is more convenient.

1. Facial Feature Extraction and Image Processing: When a face is detected, the face region of interest (ROI) with the facial features is cropped from the grayscale image. The face that was extracted is then resized to a fixed size of 50×50 pixels so that there is uniform input to the deep learning model. The CNN model will only accept RGB images, and so the extracted grayscale face is converted back into three-channel RGB. The processed images are then retained in a structured NumPy array with batch dimensions, ready for input into the CNN-based stress detection model. This is to ensure that facial data is standardized for precise predictions.

2. CNN Model Prediction: A pre-trained Convolutional Neural Network (CNN) model, already trained on facial stress datasets, is loaded to examine the captured frames. Stored facial images are input to the CNN, which processes them to predict stress levels from patterns in facial expressions learned by it. The model outputs stress scores for every frame, reflecting the probability of stress detected in the subject's face. These estimates are averaged over all frames captured to achieve a more steady and consistent stress measurement, which minimizes inaccuracies from facial expressions in moments.

3.Stress Level Calculation and Data Storage: To find the ultimate stress level, the system calculates the average of all the predicted stress scores over the captured frames. This averaging method smoothes out fluctuations and gives a more stable stress measurement. The calculated stress level is then shown on the screen and saved in a text file . This accumulated data may be used for additional analysis, long-term monitoring of stress patterns, or even with external health monitoring systems. The process may be improved by adding more physiological sensors or improving the CNN model with larger, more diverse datasets. The 3 main features considered for stress calculation are eye openness, brow furrow and mouth curvature.

Stress calculation formula:

Stress = [(0.2 × Mouth Curvature) - (0.3 × Brow Furrow Intensity) + (0.5 × Eye Openness Score)]. Average stress = sum of all stress predictions / total no.of. predictions.

Hardware part involves average stress calculation using the data obtained from facial recognition and the collected data from biometric sensors like DHT11, MAX30102 and PPG Sensor. Physical data in real time is being read directly from an individual's body. This is done with the assistance of biometric sensors such as temperature sensor, SpO2 sensor and heart rate sensor. The ambient body temperature is measured by temperature sensor DHT11 (Digital Humidity and Temperature sensor) [6]. Body temperature is different for every individual, normal body temperature is 37°C. Stress may raise temperature above 37°C or decrease below or constant.

A severely stressed individual temperature can rise beyond 41°C as well. So it simply relies on the stress level. SpO2 sensor (MAX30100) monitors the percentage of oxygen in the blood. A normal human is maintaining Oxygen Saturation level between 95% to 100%.The SpO2 level of a stressed individual may fall below 90%. It is capable of producing a severe health problem. Heart rate sensor (PPG sensor) detects the heart beat rate. 60 to 100 beats per minute is the healthy individual's normal heart beat rate while that of a stressed individual is up to 120 beats per minute.The computed stress value is compared with pre-defined threshold ranges and then the system categorizes the stress level into one of three levels: low, moderate, or high. Low stress will generally imply an acceptable state which might not call for direct action but would welcome preventive treatment such as relaxation exercises or mindfulness. Moderate stress will imply a stronger effect on the well-being of the person and will require interventions like relaxing music, deep breathing exercises, or brief pauses in order to curb stress levels. [6] Excessive stress, which is a potential threat to physical and mental well-being, can induce more intense interventions, like booking online counselling sessions, recommending professional consultations, or breathing excercises.

IV. RESULT AND DISCUSSION

A. GRAPHICAL ANALYSIS

The Training and Validation Accuracy graph shows training and validation accuracy always increasing as epochs are bigger. This means the model is doing well, and accuracy increases as it processes more data. The training accuracy, which is barely greater than the validation accuracy, indicates that the model is generalizing incredibly well to unseen data, and thus the model can be implemented for actual prediction of stress level.

The Training and Validation Loss graph indicates a linear reduction in the training loss as well as validation loss with respect to the epochs. It illustrates that the model is minimizing its errors and getting better at predicting. Validation loss ¡ training loss indicates that the model is generalizing nicely and is not overfitting. In general, the plots are indicating that the model is learning stress level trends nicely, so the model will be stable to implement in real-time monitoring systems.

Fig. 2. (a) Training and Validation Accuracy (b) Training and Validation loss

B. CONFUSION MATRIX

The model is trying very well in predicting the various levels of stress. It can be inferred from the matrix that the model is trying best in predicting low, moderate, and high levels of stress, wherein good diagonal values are the correct predictions. For instance, 4031 low stress cases and 2368 moderate stress cases are exactly predicted correctly. Likewise, 1694 severe stress cases are correctly predicted, which makes the model valid in detecting severe stress, most importantly in responding appropriately like listening to calming music or booking an online appointment.

There are also some misclassifications between nearby levels of stress, as it is natural in physiological data due to similar features. For example, moderate stress could sometimes be falsely labeled as low or high stress, and high stress could sometimes be falsely identified as moderate or extreme stress. This suggests perhaps the model requires additional fine-tuning or training data to minimize mistakes. Despite these minor misclassifications, the matrix shows overall the model is working adequately and can be employed for real-time stress monitoring and intervention.

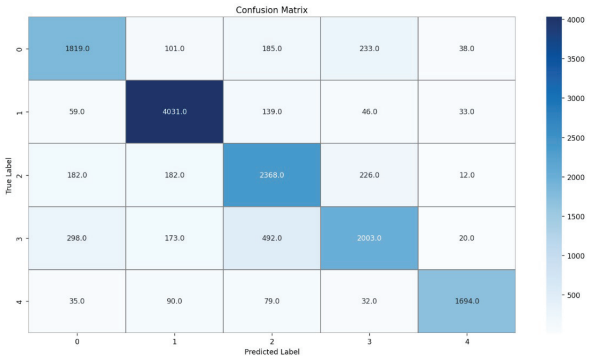

Fig. 3. Confusion matrix

C. LOW STRESS CONDITION

A happy or a neutral facial image is given as input it will the condition of low stress. The average value of low stress lies between 0 to 0.3. Low stress is a normal condition.

Fig. 4. Low stress (Average value)

D. MODERATE STRESS CONDITION

When a surprised facial expression is given as input it will become the condition of moderate stress.Breathing excercise is the remedy prescribed here. The voice assistant guides with this by counting "Breathe In" and "Breathe Out" 5 times.Breathing for few seconds can make a person feel relaxed and it reduce stress to some extend. The average value of moderate stress lies between 0.4 to 0.6.

Fig. 5. Moderate stress (Average value)

E. HIGH STRESS CONDITION

Angry or tensed facial expression is given as input. The average value of stress lies between 0.7 to 1. Playing a youtube song is one of the remedy as it can provide relief and reduce stress to some extend. But it alone cannot solve the problem so consulting a doctor would be an better option. So an automatic appointment booking system is used here.

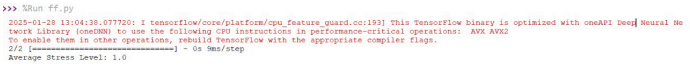

Fig. 6. High Stress (Average value)

F. SENSOR READINGS

DHT11 sensor measures the temperature value of the body. PPG sensor measures pulse rate. MAX30102 measures SPO2 and Heart rate.For a healthy adult the heart rate will be 60-100 beats per minute.Incase of a stressed person it can go above 100 beats per minute.SPO2 value for a healthy person is 95% to 100% but for a stressed person it can go below 90% .The readings obtained from various sensors:

Fig. 7. Senor readings

G. PORTABLE AI BASED VOICE ASSISTANT (HARDWARE)

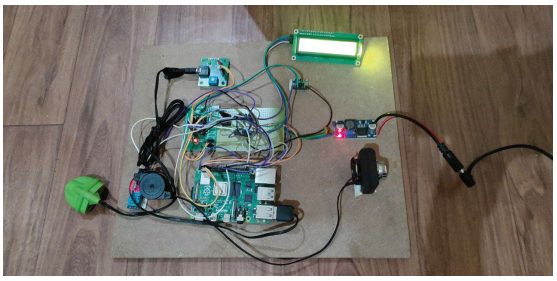

Fig. 8. Hardware model

V. CONCLUSION

The AI-based portable stress monitoring system provides a real-time, user-friendly solution for stress detection and management. Using the combination of facial recognition with CNN along with biometric sensors such as heart rate, SpO, and temperature, the device provides a holistic assessment of stress. The ability of the system to provide personal recommendations such as relaxation techniques or professional guidance enhances its practicality for daily use. With its lightweight and mobile character, it vows accessibility to individuals of any age. Analysis of the confusion matrix shows the success of the model, as well as its vulnerabilities that should be enhanced. Some of these may involve increasing the accuracy of the classification, expanding the dataset, and introducing more stress indicators. Overall, this project reflects a promising strategy towards pre-emptive stress management through AI and IoT technology.

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LICA: Logical Interactive Customer Assistant

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***Abstract*—The Logical Interactive Customer Assistant (LICA) project is an intelligent recommendation system designed to enhance the e-commerce experience by delivering personalized product suggestions to customers. With the ever-growing number of products available online, customers often struggle to find items suited to their specific needs, preferences, and lifestyles. LICA addresses this challenge by combining Web scraping, Natural Language Processing (NLP), and Large Language Models (LLMs) to offer relevant product recommendations. The project begins by gathering product data from various e-commerce sites through web scraping, collecting details on specifications, pricing, availability, and reviews. Sentiment analysis of customer reviews allows the system to assess product reliability and satisfaction, enabling it to prioritize high-quality recommendations. Through an interface supporting text input, LICA interacts with users in a natural and accessible way. This project aims to streamline online shopping by providing personalized, contextually relevant suggestions, reducing decision fatigue, and enhancing customer satisfaction in the digital marketplace.**

***Index Terms*—Large Language Model(LLM), Natural Language Processing(NLP), Application Programming Interface(API), Web Scraping, Sentiment Analysis**

I. Introduction

This project aims to provide an intelligent solution designed to enhance the online shopping experience by accurately guiding customers to products that best match their unique needs and preferences. In today's world, the sheer volume of options on e-commerce platforms can overwhelm customers, often leading to indecision or frustration. Leveraging cutting-edge web scraping techniques, LICA gathers product data from multiple e-commerce platforms, while Natural Language Processing (NLP) and Large Language Models (LLMs) enable it to understand customer-specific details—such as occupation, age, and personal preferences—to make tailored product recommendations. LICA goes a step further by conducting sentiment analysis on product reviews, empowering it to recommend items with high customer satisfaction and reliability. This sentiment-driven analysis ensures that LICA's suggestions align not only with customer needs but also with the experiences of previous buyers. Accessible through text or voice-based interactions, the Logical Interactive Customer Assistant is designed for a seamless user experience, making intelligent, context-aware recommendations that simplify decision-making in today's complex e-commerce landscape.

II. Related Works

A. *PRUS: Product Recommender System Based on User Specification and Customer Reviews [1]*

The study proposes a product recommender system that ranks products based on user-specified features and customer reviews. Unlike conventional methods, PRUS incorporates both positive and negative sentiment analysis to improve recommendation accuracy. The system extracts sentiments at the sentence level, rather than considering only the overall review

sentiment, allowing it to identify positive and negative aspects of a product separately. PRUS enables users to specify desired product features (e.g., "good battery life" or "high screen resolution"), and the system then ranks products based on how well their features match user preferences. To achieve this, the proposed RANK-ify algorithm assigns weighted values to both positive and negative sentiments of each product feature, providing users with the flexibility to adjust sentiment weights and influence the ranking list accordingly. The study used an Amazon mobile phone review dataset consisting of 316,811 reviews from 4,300 products to evaluate the effectiveness of PRUS. The system's performance was measured using Rank Score (RS) and Normalized Discounted Cumulative Gain (nDCG), demonstrating that PRUS effectively prioritizes products based on user-defined criteria and delivers personalized recommendations. The research highlights the advantages of considering both positive and negative aspects in product ranking, leading to more informed purchasing decisions.

B. A Novel Web Scraping Approach Using the Additional Information Obtained From Web Pages [2]

This study introduces UzunExt, an efficient web scraping method that improves content extraction speed without constructing a DOM tree. Traditional web scraping methods use DOM-based extraction, where a web page's Document Object Model (DOM) tree is created, and the necessary data is accessed by traversing this tree. However, this approach is computationally expensive and time-consuming, particularly for large-scale data extraction tasks. Instead, UzunExt employs string-based methods that locate and extract content using pattern matching, additional metadata, and optimized search techniques. The approach involves extracting three key metadata points during web crawling: starting position (to accelerate searches), inner tag count (to refine extraction boundaries), and tag repetition (to avoid redundant parsing). Experiments show that UzunExt is 60 times faster than conventional DOM-based methods and improves extraction time by 2.35 times when using additional metadata. The paper also explores search algorithms, the impact of HTML tag types on performance, and integration methods for existing web scrapers. UzunExt's efficiency makes it highly adaptable for applications like search engines, sentiment analysis, and market monitoring.

C. Analyzing Public Sentiment on the Amazon Website: A GSK-Based Double Path Transformer Network Approach for Sentiment Analysis [3]

This study presents an advanced sentiment analysis model for processing Amazon customer reviews. The study introduces a Double Path Transformer Network (DPTN), designed to enhance text classification by integrating self-attention and convolutional neural networks (CNNs) in a dual-path architecture. This model captures both global and local contextual features, improving sentiment classification accuracy. The authors leverage the Gaining-Sharing Knowledge (GSK) optimization technique to fine-tune hyperparameters, optimizing performance and addressing class imbalance issues without explicit balancing techniques. The study evaluates its approach using multiple Amazon review datasets, achieving a notably high accuracy of 95 percent, outperforming traditional models like Support Vector Machines (SVM), Deep Belief Networks (DBN), and CNN-based classifiers. The paper details preprocessing techniques, including punctuation removal, tokenization, and word embedding strategies (Word2Vec, GloVe, BERT, FastText) for feature extraction. Additionally, it discusses the mathematical formulation of the DPTN model, including multi-head attention mechanisms, bidirectional feature interactions, and hybrid transformer blocks. The research concludes that the proposed method significantly enhances sentiment analysis accuracy and efficiency, making it an effective tool for analyzing large-scale user-generated text data in e-commerce.

D. NLP-Based Recommendation Approach for Diverse Service Generation [4]

This research paper explores the use of Natural Language Processing (NLP) techniques in recommendation systems, particularly for predicting user purchases based on historical data. The study focuses on tokenizing product names rather than using full names, enabling a deeper understanding of product relationships. By applying n-grams (unigrams, bigrams, and trigrams), the model identifies hidden connections between products, facilitating improved recommendations. The authors compare tokenized and non-tokenized approaches using datasets from UK e-Commerce and Instacart, demonstrating superior performance of the tokenized model in terms of Hit-Rate and Mean Reciprocal Rank (MRR). The study also proposes two novel applications: New Product Brainstorming, which generates innovative product names by analyzing tokenized patterns, and Keyword Trend Forecasting, which predicts emerging consumer trends based on keyword frequency. The findings emphasize the potential of NLP-based recommendation systems in e-commerce, offering improved personalization and market trend insights without relying on personal user data. Future work includes expanding datasets and refining NLP techniques to enhance recommendation accuracy and adaptability.

III. Proposed Work

A. System Architecture

The system is implemented as a website that consists of two primary pages: a search page where users can enter a product query and a results page where the recommended products are displayed. The backend of the system integrates multiple APIs and services to facilitate data retrieval, processing, and recommendation generation. The frontend interacts with the backend through API calls, ensuring a smooth and efficient data flow between the user interface and the recommendation engine.

B. Workflow

The workflow begins with the user entering a product query in the search bar on the website. Once submitted, the query is processed and sent to the backend, where the system initiates web scraping to collect relevant product details from the Amazon shopping website using Scraper API. The extracted product data includes attributes such as product name, price, description, customer ratings, review count, product image, and a direct product link.

After collecting the necessary data, the system utilizes Perplexity's LLaMA API to analyze and rank the products based on customer ratings and review counts. The AI model processes the scraped data and selects the highest-rated products, ensuring that only the most recommended items are presented to the user. The recommended products are then formatted and displayed on the results page of the website, where users can view detailed product information, including an image, name, price, customer rating, and a direct link to the product on Amazon. The user interface is designed to be intuitive and engaging, allowing users to quickly and easily find high-quality products. The workflow of the entire project is shown in fig 1.

1) Web Scraping Process Using Scraper API: The web scraping process involves several key steps to ensure the extraction of accurate and relevant product data from the Amazon shopping website. First, the backend Flask server constructs an API request with the user's search query, specifying parameters such as search keywords and pagination options. The Scraper API then sends this request to Amazon's search engine, retrieves the product listings, and extracts key details, including product name, price, description, customer ratings, review count, product image URL, and a direct product link. If multiple pages of results exist, the API iterates through additional pages to ensure a comprehensive dataset is collected.

Once the data is retrieved, it undergoes a cleaning and structuring process to remove unnecessary elements and standardize the format. This ensures consistency in numerical values, such as price and ratings. The structured product data is then stored in the SQLAlchemy database or directly sent to the Perplexity LLaMA API for ranking based on customer ratings.

2) Product Ranking Process Using LLaMA API: The ranking process performed by the LLaMA API ensures that only the most relevant and highest-rated products are recommended to the user. After retrieving product data from the Scraper API, the system feeds this data into the LLaMA model for analysis. The ranking process involves the following steps:

Preprocessing the Data: The extracted product information, including product name, rating, review count, and other relevant metadata, is cleaned and structured to ensure consistency.

Feature Extraction: The AI model identifies key features such as customer ratings, the number of reviews, and potential keyword relevance to determine product quality and popularity.

Weight Assignment: The ranking algorithm assigns weights to different factors, prioritizing products with higher customer ratings and a significant number of reviews, which indicates trustworthiness.

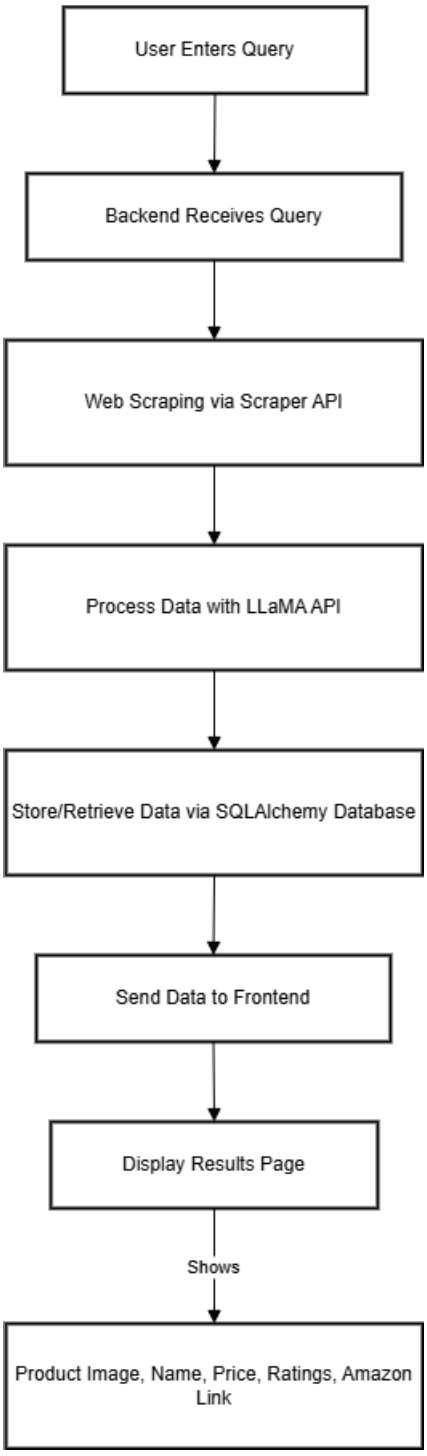

Fig. 1. LICA WORKFLOW DIAGRAM

Scoring and Ranking: The AI model computes a final score for each product based on weighted attributes, sorting the products from highest to lowest score.

Filtering and Selection: The top-ranked products are selected for display, ensuring that the user is presented with

only the best recommendations.

C. Technology Stack

The frontend of the system is built using React.js, providing a dynamic and responsive user experience. The backend is developed using Python with Flask, handling data processing, API calls, and system logic efficiently. SQLAlchemy is used as the database ORM, enabling seamless interaction with the database for storing and retrieving product data. The system integrates two key APIs: Scraper API, which enables web scraping of Amazon product details, and Perplexity's LLaMA API, which performs AI-based product ranking.

IV. Results

The User enters the product query on the home page as shown in figure 2. The system successfully scrapes relevant

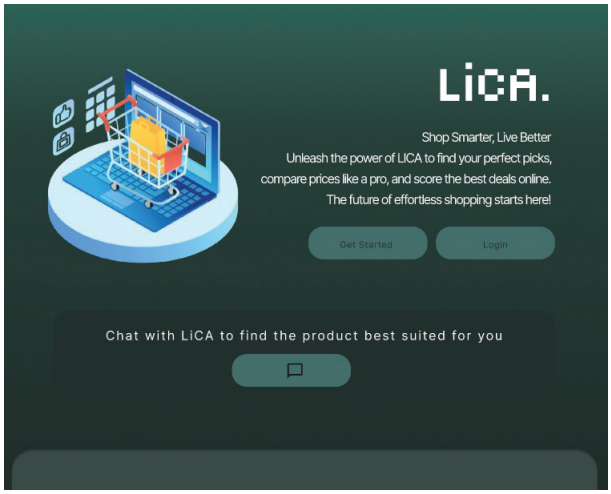

Fig. 2. HOME PAGE

product details from Amazon using Scraper API, including product name, price, customer ratings, review count, and images. This data is then processed through Perplexity's LLaMA API, which ranks the products based on predefined criteria such as customer feedback, rating scores, and review volume as shown in fig 3 and fig 4.

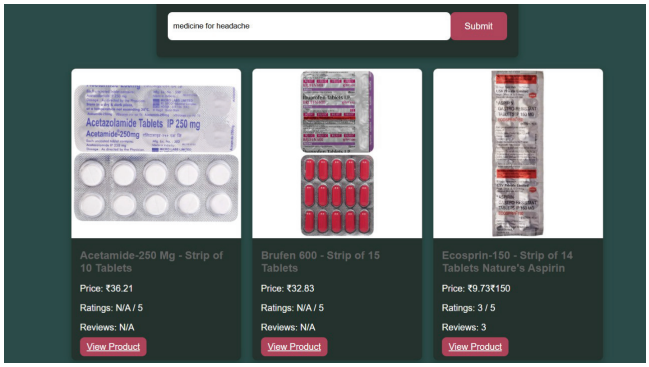

Fig. 3. RESULT PAGE 1

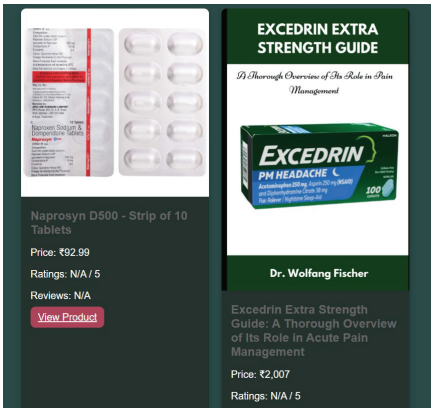

Fig. 4. RESULT PAGE 2

V. Conclusion

LICA provides an intelligent solution for assisting users in finding the right products by leveraging web scraping and AI-powered selection. By integrating Scraper API for real-time data extraction and LLaMA API for ranking products based on customer ratings, the system ensures that users receive accurate and relevant recommendations. The user-friendly interface and seamless backend processing make the system an effective tool for enhancing the online shopping experience.

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Developing Tactics, Techniques, and Procedures (TTPs) for Open-Source Web Security

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***Abstract*—Open-source web applications play a crucial role in modern digital ecosystems, yet they often face security challenges due to limited vulnerability detection mechanisms. This paper presents a systematic approach to web application penetration testing on open-source projects, integrating both automated and manual security assessments. Using tools like OWASP ZAP and Burp Suite, automated scanning helps identify common vulnerabilities, including improper authentication, Cross-Site Scripting (XSS), SQL injection, and misconfigurations. To enhance accuracy, manual testing is conducted to validate and exploit detected vulnerabilities, ensuring a more comprehensive security evaluation. A key contribution of this work is the development of a structured Tactics, Techniques, and Procedures (TTPs) framework to document and categorize vulnerabilities systematically, addressing the absence of standardized methodologies for open-source security. The findings highlight critical security gaps in widely used open-source projects and emphasize the importance of combining automated tools with manual expertise for effective vulnerability management. By bridging the research gap in open-source security testing, this study provides valuable insights and recommendations for developers, security professionals, and researchers to enhance the resilience of open-source applications against cyber threats.**

***Index Terms*—Open-source security, Web application penetration testing, Vulnerability assessment, OWASP ZAP, Bug bounty, Security misconfigurations, TTP framework.**

I. Introduction

The exponential development of digital ecosystems has fueled the global use of web applications across industries, allowing businesses, organizations, and individuals to communicate smoothly over the internet. Open-source web applications, in specific, are at the forefront of today's software development, providing accessibility, flexibility, and open-ended community-driven improvements. Such applications are enhanced by open source code, enabling developers to change and enhance functionalities while promoting collaboration within the international software community. But even with such benefits, open-source web applications are extremely vulnerable to security loopholes because they are open to the public and because contributors vary in their security awareness. Web application security incidents have grown drastically in recent years with attackers using flaws like Cross-Site Scripting (XSS), SQL injection, misconfiguration, and ineffective access controls.

Most open-source projects do not have specific security teams or defined vulnerability assessment methodologies, which renders them easy targets for cyber attacks. Lack of a unified methodology for security tests also makes it harder to guarantee thorough protection against prospective exploits. The aim of this research is to bridge the gap of open-source security scanning by incorporating automated security scanning tools with manual security testsin order to generate a more thorough and precise review of vulnerabilities. Automated software like OWASP ZAP and Burp Suite is popularly employed for preliminary security scanning, systematically recognizing common loopholes in web applications.

In order to counter these limitations, manual penetration testing is performed to validate, exploit, and verify security vulnerabilities, which makes the evaluation more reliable. One of the main contributions of this research is the establishment of a Tactics, Techniques, and Procedures (TTPs) framework, a structured approach that categorizes and documents open-source web application vulnerabilities systematically. The framework improves the effectiveness and consistency of security testing by offering a standardized method of risk identification, classification, and mitigation. By integrating automation, manual skills, and structured documentation, this research aims to define a more robust and replicable method of securing open-source web applications. [1].

II. Related Work

Web application security has been a significant research focus, with various studies exploring penetration testing method-

ologies, security evaluation tools, and bug bounty programs. Existing research has primarily concentrated on proprietary web applications, leaving open-source applications underereserved in terms of structured security assessment frameworks.

Several studies have analyzed the effectiveness of web security evaluation tools. Shi et al. [2] conducted an analysis of web security tools, highlighting their capabilities in detecting vulnerabilities such as SQL injection and Cross-Site Scripting (XSS). Alzahrani et al. [3] compared multiple security tools and found variations in their detection accuracy and false positive rates. These studies emphasize the need for a combined approach using both automated and manual testing to improve security evaluations.

Penetration testing frameworks provide structured methodologies for security assessments. Selvam and Senthilkumar [1] proposed a web service-based vulnerability testing framework to improve penetration testing efficiency. De Jimenez [4] demonstrated the practical applications of ethical hacking techniques in penetration testing, reinforcing the importance of standardized methodologies.

Bug bounty programs have emerged as an effective means of crowdsourcing security assessments. Magazinius et al. [5] mapped the benefits and limitations of bug bounty programs, while Walshe and Simpson [6] analyzed their role in enhancing security through community-driven vulnerability detection. These studies suggest integrating bug bounty methodologies with penetration testing to enhance the security of open-source web applications. [7]

Several standardized record of Vulnerability is maintained in National Vulnerability Database that is accessible to the community. Each reported security flaw's detail can be fetched through Common Vulnerability and Exposures ID. This database is recorded for more than a decade and the detailed analysis of the reported security flaws helps network administrators and security professionals to enhance the cybersecurity practices in an organization [8]

Many individuals, groups, organizations or governments use web applications as a means to exchange information or support business-related tasks. Despite the increased adoption, web applications use is however directly associated with comparable threats and attacks. With the increasing threats and attacks on web applications, organizations require a more effective concept of web application security. Web Application Firewall (WAF) is a security concept that can be used to prevent various threats and attacks on web applications.

Existing research has contributed significantly to web application security through automated tools, penetration testing frameworks, and bug bounty programs. However, the lack of standardized methodologies for open-source security assessments remains a gap. This study builds upon prior work by integrating automated scanning tools with manual validation and proposing a structured Tactics, Techniques, and Procedures (TTP) framework to address open-source security challenges effectively. [9]

Other research paper proposes a framework for testing security vulnerabilities based on publicly known security vulnerabilities database. After vulnerabilities are found in application, the security tester uses Penetration testing tools to test the security flow.

In this paper they ensemble machine learning is an adequate technique for automated vulnerability type classification and also achieved noticeably better prediction scores compared to basic machine learning methods, using improved training features and ensemble machine learning algorithms. [10]

Mobile users are increasingly becoming targets of malware infections and scams. In order to curb such attacks it is important to know how these attacks originate. We take a previously unexplored step in this direction. Numerous in-app advertisements work at this interface: when the user taps on the advertisement, she is led to a web page which may further redirect until the user reaches the final destination. Even though the original applications may not be malicious, the Web destinations that the user visits could play an important role in propagating attacks. We develop a systematic static analysis methodology to find ad libraries embed in applications and dynamic analysis methodology consisting of three components related to triggering web links, detecting malware and scam campaigns, and determining the provenance of such campaigns reaching the user. [11]

The paper surveys various frameworks that can be secured at the testing level using penetration testing approaches. Penetration testing, also known as ethical hacking, is a proactive security measure where simulated attacks are conducted to identify and address vulnerabilities before they can be exploited by malicious actors. This process is integral to security quality assurance, ensuring that systems are robust against potential threats. [12].

The paper investigates the security risks associated with mobile banking on Android platforms, focusing on the Anubis Trojan malware.This research contributes to the understanding of Trojan malware on the Android operating system, highlighting the need for enhanced security measures in mobile banking applications. [13]

The paper focuses on assessing the security of Docker containers using penetration testing techniques. The authors aim to identify potential vulnerabilities within Docker environments to enhance overall system security.This research underscores the importance of proactive security measures in the deployment and management of Docker containers, highlighting the need for continuous assessment and improvement to safeguard against emerging threats. [14].

The paper focuses on analyzing the Common Vulnerabilities and Exposures database to enhance cybersecurity measures. The authors employ topic modeling techniques to categorize and understand patterns within the CVE entries. This approach aids in identifying prevalent vulnerability themes, facilitating more efficient vulnerability management and threat mitigation strategies. By classifying vulnerabilities into distinct topics, organizations can prioritize their security efforts based on the most pressing threats identified in the CVE database. It offers a structured perspective on vulnerability data, enabling more proactive and informed cybersecurity practices. [15]

III. Methodology

This study employs a systematic penetration testing approach, comprising the following key steps:

A. Selection of Open-Source Web Applications

Initially, a diverse set of open-source web applications is selected based on their popularity, active development, and relevance to real-world scenarios. The selection ensures a variety of application types and technology stacks to facilitate a comprehensive evaluation.

B. Automated Vulnerability Scanning

Next, automated security tools such as OWASP ZAP and Burp Suite are utilized to scan the selected applications for common vulnerabilities. These tools help detect issues such as SQL injection, Cross-Site Scripting (XSS), security misconfigurations, and weak authentication mechanisms. The results provide an initial insight into potential security flaws.

C. Manual Validation of Vulnerabilities

To ensure accuracy, manual testing follows automated scans. Security experts validate identified vulnerabilities by attempting controlled exploits to assess their severity and real-world impact. This step is crucial as automated tools may produce false positives, requiring human expertise for confirmation.

D. Structured Documentation Using the TTP Framework

All identified and validated vulnerabilities are documented in a structured Tactics, Techniques, and Procedures (TTP) framework. This categorization enhances clarity by outlining the vulnerability type, impact assessment, and recommended mitigation strategies, ensuring consistency in reporting.

E. Comprehensive Reporting and Security Recommendations

Finally, the findings are compiled into a detailed report, including risk assessments, proof-of-concept exploits (where applicable), and actionable mitigation strategies. The objective is to provide security professionals and developers with clear insights to enhance web application security.

By integrating automated scanning with expert manual validation, this methodology ensures a thorough and systematic approach to penetration testing, yielding reliable and actionable security evaluations.

IV. Results and Discussion

The penetration testing process uncovered several common vulnerabilities across multiple open-source projects, including:

A. Personally Identifiable Information (PII) disclosure

Personally Identifiable Information (PII) disclosure" refers to the act of revealing or sharing information that can be used to identify a specific individual, such as a name, address, phone number, or social security number, without proper authorization, potentially leading to identity theft or other privacy concerns if not handled securely; essentially, it means exposing someone's personal details in a way that could be harmful to them.

	critical	medium	low
adobe	-	4	4
automattic	2	9	7
bitwarden	-	8	9
brave	1	6	3
chia network	-	2	2
discourse	-	4	5
gitlab	-	7	9
kubernetes	1	5	6
leather	-	5	4
mapbox	-	4	3
metamask	1	3	6
polygon technologies	-	3	2
tools for humanity	1	7	8
wordpress	1	7	5

TABLE I
SECURITY ISSUE CLASSIFICATIONS

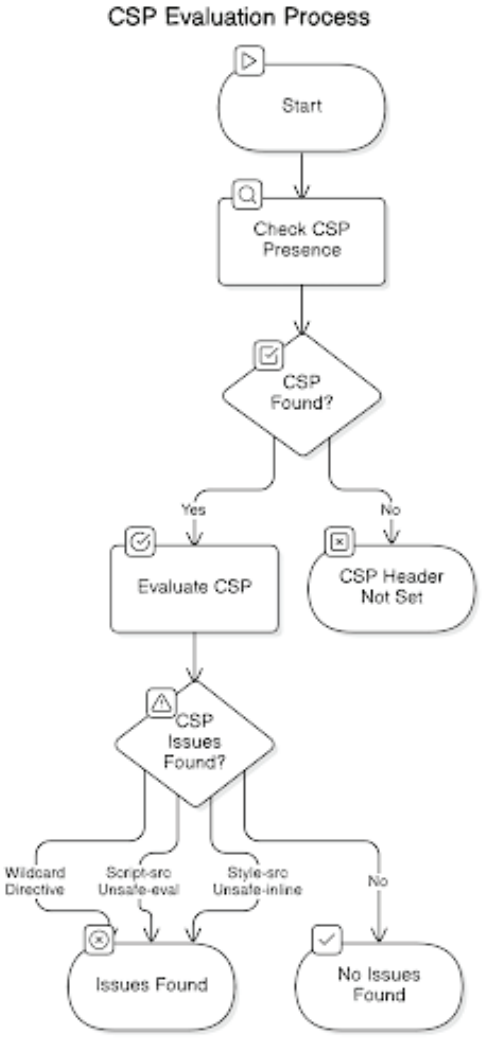
B. Hidden files and security misconfigurations

Hidden files and security misconfiguration are significant vulnerabilities that can expose systems to attacks. Hidden files, often containing sensitive information like passwords or API keys, may be overlooked in security scans, leaving them vulnerable to unauthorized access. Misconfigurations, such as default credentials, exposed cloud storage, or excessive user privileges, can increase an attack surface and lead to data breaches, privilege escalation, or system disruptions. To mitigate these risks, it's essential to implement proper access controls, regularly audit configurations, enforce the principle of least privilege, and use security tools to monitor for misconfigurations and potential threats.

C. Content Security Policy (CSP) header misconfigurations

A Content Security Policy (CSP) header misconfiguration refers to an incorrectly set CSP header on a website, where the rules defining allowed sources for scripts, styles, images, and other resources are too permissive, potentially allowing malicious content to load and compromising the website's security.

This misconfiguration can occur when wildcard (*) sources, overly broad domains, or unsafe directives like unsafe-inline and unsafe-eval are used, making it easier for attackers to inject and execute malicious scripts. As a result, vulnerabilities such as cross-site scripting (XSS) can be exploited, leading to data theft, session hijacking, or defacement of the website. To mitigate these risks, developers should implement a strict CSP policy by specifying trusted domains, avoiding inline scripts and styles, and regularly reviewing and updating security policies to adapt to emerging threats.



D. Cross-domain misconfigurations

Cross-domain misconfiguration occurs when a web application or service improperly handles cross-origin resource sharing (CORS) policies, allowing unauthorized or malicious domains to access sensitive resources. CORS is a security feature that restricts how resources on a web server can be requested from another domain. A misconfigured CORS policy, such as overly permissive settings (e.g., allowing any origin or improper handling of credentials), can expose sensitive data, allowing attackers to bypass same-origin policies and access restricted information from other domains. This can lead to data leaks, cross-site scripting (XSS) attacks, or other forms of exploitation. Mitigation involves configuring strict CORS settings, only allowing trusted domains, and ensuring that sensitive data is properly secured against unauthorized cross-domain requests. These findings highlight the importance of combining automated tools with manual security assessments to achieve a comprehensive evaluation. Additionally, the implementation of a structured TTP framework provides a systematic way to document and classify vulnerabilities, contributing to the overall security of open-source web applications.

V. Summary of Findings

A. Misconfigured Configuration Files (CWE-16)

Affected Host: https://prow.k8s.io/config
Impact: Critical — **Likelihood:** Moderate
Observation: Misconfigured files expose sensitive settings, increasing the risk of unauthorized access.
Recommendation: Apply security best practices for configuration management.

B. Exposure of Sensitive Data in Public Logs (CWE-200)

Affected Host: https://prow.k8s.io/view/gs/kubernetes-ci-logs
Impact: Critical — **Likelihood:** High
Observation: Publicly accessible logs may contain sensitive information exploitable by attackers.
Recommendation: Implement access controls and encryption mechanisms.

C. Improperly Implemented Security Checks (CWE-358)

Affected Host: https://k8s.io
Impact: High — **Likelihood:** Moderate
Observation: Weak security checks allow unauthorized operations, leading to breaches.
Recommendation: Follow security best practices and address security gaps.

D. Cross-Site Scripting (XSS) Vulnerability (CVE-2024-6484)

Affected Host: https://kubernetes.io (Bootstrap 4.6.2)
Impact: Moderate — **Likelihood:** High
Observation: XSS vulnerabilities allow attackers to inject malicious scripts, compromising user data.
Recommendation: Implement input validation and enforce Content Security Policy (CSP).

VI. Tactics, Techniques, and Procedures (TTPs)

A. Modify System Configuration for Defense Evasion

Tactic: Defense Evasion — **Technique:** Modify System Configuration
Observation: Attackers exploit misconfigurations to bypass security and escalate privileges.
Recommendation: Strengthen configuration management and enforce logging policies.

B. Unsecured Credentials Exposure

Tactic: Credential Access — **Technique:** Unsecured Credentials Exposure
Observation: API keys and authentication credentials may be exposed in misconfigured storage or public repositories.
Recommendation: Secure credential storage and scan for exposed secrets.

C. Web Application Exploitation (XSS)

Tactic: Initial Access — **Technique:** Web Application Exploitation (XSS)
Observation: Attackers use XSS to inject scripts, steal session cookies, and manipulate user actions.
Recommendation: Implement input validation and deploy CSP.

VII. Conclusion and Future Work

This research emphasizes the significance of penetration testing in the improvement of the security of open-source web applications. Through the combination of automated security scanning tools and manual testing methods, we were able to detect severe vulnerabilities that may potentially threaten popular open-source projects. The implementation of a Tactics, Techniques, and Procedures (TTP) framework offers a formalized and standardized approach to security testing, complementing existing vulnerability detection methods. The results highlight that a multi-layered security approach, integrating tools such as OWASP ZAP and Burp Suite with skilled manual validation, is critical to enhancing detection rates and reducing false positives. In addition, the TTP model provides a systematic and reproducible methodology for documenting and categorizing security vulnerabilities, supporting security professionals and developers in addressing threats more effectively.

By formulating a penetration testing standard method, this study supports the overall body of cybersecurity and offers actionable advice for hardening open-source applications. Future studies should aim to extend penetration testing scope, improve the TTP framework to be consistent with industry standards, and incorporate machine learning algorithms to improve the accuracy of detected vulnerabilities. Furthermore, integrating bug bounty programs and security programs driven by the community would further bolster the security position of open-source projects. As cyber threats evolve further, ongoing research and updating of security measures will remain critical to the protection of open-source web applications against new threats. The quick development of **AI-based attacks, cloud security issues, and advanced malware requires ongoing development of penetration testing techniques. Through joint security initiatives, with advanced automation tools, and by supporting proactive threat detection, open-source development can gain higher immunity to cyber threats, creating a safer digital environment.

In addition, cooperation among open-source communities, cybersecurity experts, and industry professionals can create a shared security model, where the knowledge, tools, and best practices are repeatedly updated and refined. Through a focus on security awareness, training of developers, and ongoing improvement, the ultimate objective is the development of a scalable and sustainable security framework that not only counters present vulnerabilities but also responds to future cybersecurity threats, which will keep open-source web applications secure in an increasingly dynamic threat environment.

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A Versatile LoRa-Based IOT System for Data Acquisition, Rescue, Management and Control of Disaster

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***Abstract*— This project presents a versatile IoT system that leverages LoRa technology for data acquisition in large geographical areas, rescue operations, management, and control in remote and challenging environments. This general-purpose system is designed to operate in areas lacking cellular or internet connectivity such as forests, deserts, maritime zones, harbours and isolated infrastructures enabling applications across various domains. The implementation is done using long range low power wireless network using technologies like Lora, which can be connected like a network or as repeaters. By utilizing a modular sensor architecture, the system can collect real time data on environmental parameters, geo-spatial information, infrastructure health. For example, parameters like temperature, pressure, humidity, vibration tilt etc. by changing the input sensor type. The collected data is transmitted through a LoRa network to a central cloud server for storage, analysis, and remote management. By employing advanced analytics, the system can predict natural disasters, monitor environmental condition and support efficient rescue operations. Other key applications include scientific research, military surveillance, weather forecasting, disaster management, infrastructure monitoring and alarming. The project aims to demonstrate the system's effectiveness in providing real-time data and insights for decision-making in remote and inaccessible regions.**

Keywords*— *IoT system, LoRa technology, data acquisition, remote monitoring, low power, real-time data, cloud server, disaster management, infrastructure monitoring, weather forecasting, decision-making.

I. INTRODUCTION

The increasing demand for efficient and sustainable energy solutions has led to a significant shift toward IoT-based monitoring systems for real-time data acquisition and analysis. LoRa technology, with its low power and long-range communication capabilities, has emerged as a key enabler for remote monitoring applications. This system focuses on environmental monitoring, disaster prediction, and infrastructure management, leveraging wireless sensor networks to collect real-time data from harsh and remote locations.

With advancements in power-efficient microcontrollers, sensors, and cloud computing, the proposed system provides a cost-effective and scalable approach for long-range data transmission without relying on existing cellular or internet infrastructure. This is especially beneficial in disaster-prone areas, military surveillance, and remote industrial operations, where traditional networks are unreliable or unavailable.

By utilizing a modular sensor architecture, the system adapts to various applications, including temperature, pressure, humidity, and structural health monitoring. The collected data is processed and transmitted through LoRa networks to a central cloud platform, ensuring real-time decision-making and predictive analytics for disaster management and resource optimization.

Despite the numerous benefits, challenges remain in terms of network scalability, power consumption, and data security. Addressing these concerns will be essential in advancing future IoT-based environmental monitoring systems, ensuring reliability and efficiency in large-scale locations, capable of collecting real-time data on environmental parameters such as temperature, humidity, pressure, and structural integrity. These nodes communicate with a central LoRa gateway, which transmits the data to a cloud-based platform for storage, analysis, and visualization.

The system ensures continuous monitoring, enabling early detection of natural disasters, infrastructure failures, and environmental hazards. Additionally, real-time alerts and predictive analytics help authorities take proactive measures, improving disaster response and resource management.

With its low-power design, adaptability to various use cases, and minimal maintenance requirements, LoRaX provides a reliable and efficient solution for monitoring in disaster-prone, off-grid, and connectivity-deprived regions.

II. METHODOLOGY

A. System Architecture

The proposed LoRa-based IoT system consists of two primary components: the Field Station and the Base Station, which work together to collect, transmit, and analyze environmental and structural data.

The Field Station is responsible for data acquisition and transmission. It includes an ESP32 microcontroller interfaced with environmental sensors such as temperature, humidity, pressure, vibration, and displacement sensors. The collected sensor data is processed and transmitted using an SX1276 LoRa transceiver. A Li-Po battery with an LM7805 voltage regulator ensures continuous operation, while an SMA antenna enhances long-range data transmission efficiency. The Base Station receives data from the Field Station via a LoRa Gateway. The received data is processed and stored on a cloud-based platform (AWS IoT Core), enabling real-time analysis. A threshold-based anomaly detection system is implemented, which generates alerts through SMS, email, or mobile applications when critical sensor readings are detected.

B. Data Transmission and Processing

The communication between the Field Station and the Base Station is facilitated through LoRa technology, which ensures long-range, low-power data transmission. The SX1276 transceiver module is used for efficient wireless communication. Unlike conventional LoRaWAN implementations, the proposed system operates as a standalone LoRa network, eliminating dependency on pre-existing infrastructure. Upon reception at the Base Station, the data is transmitted to the cloud for real-time processing. The cloud-based analytics module applies machine learning algorithms for anomaly detection and predictive analysis, enabling early warnings for environmental hazards. The data is visualized through an interactive dashboard, providing users with real-time monitoring capabilities.

C. Power Management

The system is designed with a focus on low-power consumption to ensure prolonged operation in remote areas. A battery monitoring circuit continuously tracks voltage levels and triggers power-saving mechanisms when required. An adaptive duty cycle approach is implemented to optimize energy usage by regulating sensor activation intervals based on environmental conditions.

D. Implementation and Performance Evaluation

The system undergoes multiple phases of simulation, prototype testing, and real-world deployment to ensure reliability and efficiency.

In the simulation phase, the Proteus and MATLAB platforms are used to validate circuit design, sensor functionality, and data transmission reliability. The prototype development phase involves integrating the LoRa communication module with the sensor network to verify end-to-end connectivity and cloud data synchronization. For field deployment, the system is tested in real-world remote environments to evaluate signal strength, latency, packet delivery ratio (PDR), and power consumption. The results are analyzed to refine system performance, ensuring optimal functionality in disaster-prone and connectivity-deprived areas.

E. Block Diagram

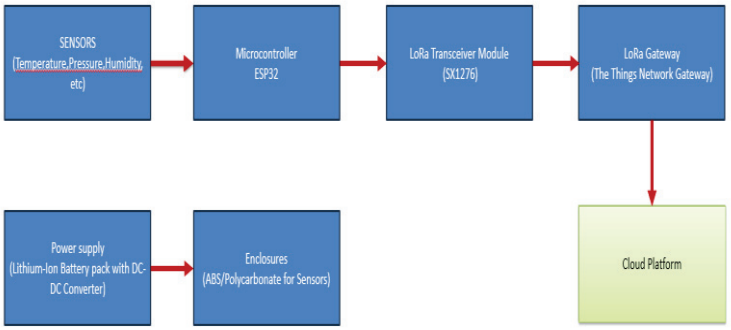

Fig. 1. LoRaX Block Diagram

Fig.1 Shows the Sensors collecting real-time data such as temperature, humidity, and pressure, which is then processed by the ESP32 microcontroller. The processed data is transmitted via a LoRa transceiver to a LoRa Gateway (The Things Network Gateway), which forwards it to a cloud platform like AWS IoT Core. Finally, the collected data is stored and analyzed for insights, enabling efficient remote monitoring in low-power, long-range communication systems.

F. Flow Chart

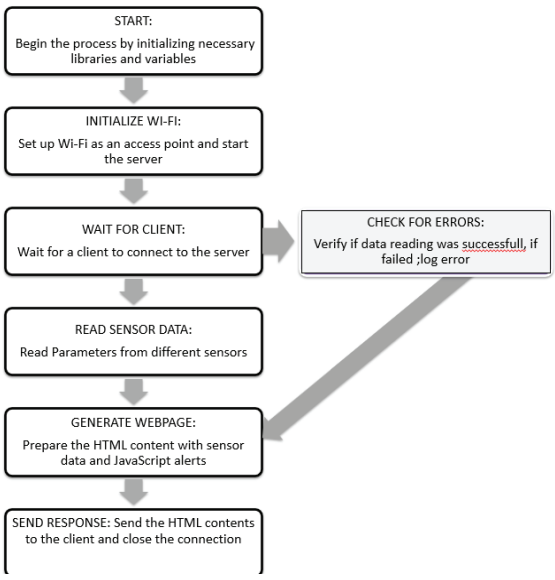

Fig. 2. LoRaX

The flowchart outlines the process of sensor data acquisition and transmission in a LoRa-based IoT system. It starts with system initialization, Wi-Fi setup, and client connection. Sensor data is then read, verified for errors, and logged if necessary. The data is used to generate an HTML webpage with JavaScript alerts, which is sent to the client before closing the connection. This ensures efficient data monitoring and real-time visualization.

III. SIMULATION

A. Proteus Model

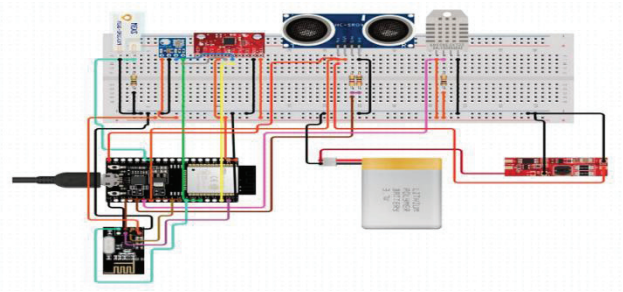

Fig. 3. Receiving and Transmitting Part

B. Component Specification

1) Microcontroller (ESP32): The ESP32 is the core processing unit of the system, equipped with dual-core processing, Wi-Fi, and Bluetooth capabilities. It operates at 240 MHz and features multiple GPIOs, ADCs, and UART interfaces for seamless integration with sensors and communication modules. Its low-power consumption and deep-sleep mode make it ideal for battery-operated applications.

2) LoRa Transceiver: The LoRa transceiver enables long-range wireless communication, operating at frequencies such as 433 MHz, 868 MHz, or 915 MHz, depending on the region. It provides a high link budget and spread-spectrum modulation for robust data transmission in remote locations with minimal power consumption.

3. Environmental Sensors (DHT11, MPU6050, Soil Moisture Sensor): Various sensors are used to monitor environmental parameters. The DHT11 measures temperature and humidity with high accuracy. The MPU6050 is a 6-axis motion tracking device, combining a 3-axis gyroscope and a 3-axis accelerometer, which helps in detecting movements, vibrations, and tilts. A soil moisture sensor helps in agricultural applications by determining soil water levels.

4. LoRa Gateway: The LoRa gateway acts as a bridge between LoRa nodes and the cloud platform, aggregating data from multiple devices and forwarding it to AWS IoT Core. It supports multiple frequency bands and provides a reliable uplink/downlink for long-range applications.

5. Power Supply (Li-ion/Li-Po Battery, Voltage Regulators): A rechargeable Li-ion or Li-Po battery (3.7V, 2500mAh or higher) powers the system, ensuring continuous operation. For sustainable applications, a solar panel (5V-12V) is used for energy harvesting. Voltage regulators like AMS1117 and MP1584 maintain a stable power supply for connected components.

6. Cloud Platform (AWS IoT Core, Firebase): The cloud platform processes and stores real-time sensor data. AWS IoT Core provides MQTT-based data transmission, while DynamoDB and S3 store structured and unstructured data. Firebase is used for real-time database applications, ensuring seamless remote access and visualization.

7. Data Visualization (Website using HTML, CSS): The collected sensor data is visualized through a custom-built website using HTML and CSS. This web-based interface provides an interactive and user-friendly dashboard, allowing real-time monitoring of environmental parameters. The website is designed for responsiveness and ease of access, ensuring seamless data interpretation from any device.

C. Simulation Result

The simulation result without using WIFI/Internet is verified by Proteus and the results are shown below.

1) Temperature and Humidity

Temperature and Humidity reading is shown in Figure.4

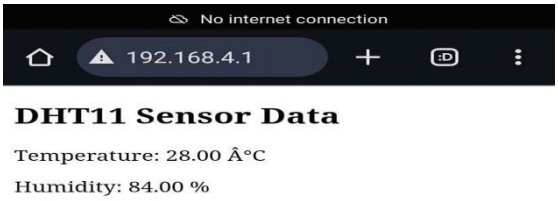

Fig. 4. DHT11 Sensor Data

2) Basic Warning System

Warning system result is shown in Figure.5

Fig. 5. Warning System

3) Sensor Integration

Sensor integration is shown in Figure.6

Fig. 6. Sensor Integration

4) Website

Simple website view is shown in Figure.7

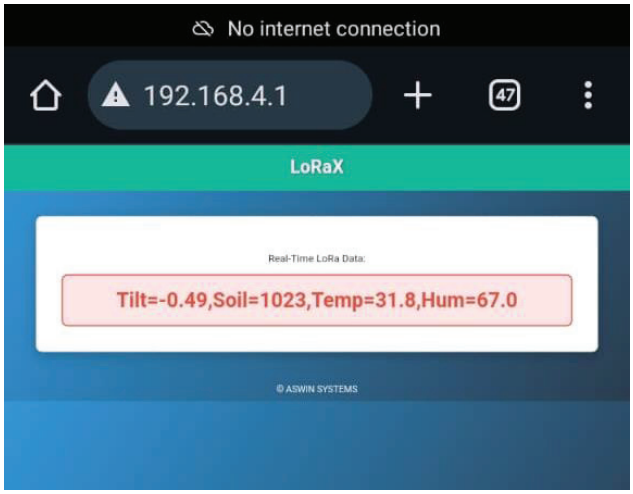

Fig. 7. Website view

5) Product View

Product view is shown in Figure 8

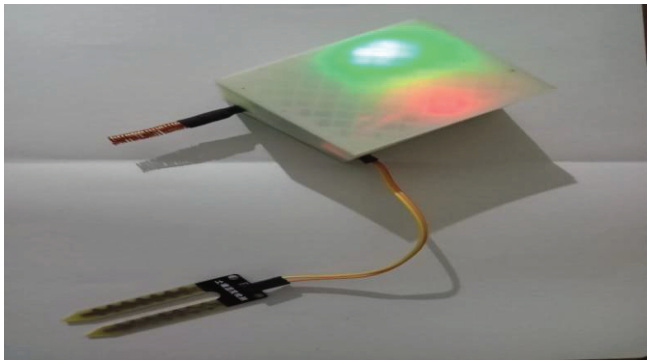

Fig 8. Product View

IV. CONCLUSION

The LoRaX project successfully demonstrates the potential of using LoRa technology for real-time environmental monitoring, disaster management, and infrastructure health assessment. By leveraging long-range, low-power communication, the system ensures efficient data acquisition and transmission in remote areas without relying on conventional internet connectivity. The integration of modular sensors and cloud-based analytics enhances real-time decision-making, allowing early detection of critical environmental changes. This project lays the foundation for scalable and sustainable IoT-based solutions in various domains, including agriculture, industrial monitoring, and disaster response. Future enhancements can include AI-driven predictive analytics and expanded sensor networks for broader applications.

V. ACKNOWLEDGMENT

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A Dual-Controlled Prosthetic Arm: EMG and Voice-Driven Approach for Upper Limb Restoration

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Abstract*— This paper presents a novel approach to prosthetic arm control by integrating ElectroMyoGraphy (EMG) signals and voice recognition, enhancing usability, reliability, and affordability. The system primarily utilizes EMG signals to detect muscle movements, enabling natural and intuitive hand control. However, prolonged EMG use may lead to muscle fatigue, causing signal distortion and reduced accuracy. To address this, a voice module is incorporated, allowing users to switch to voice control when fatigued or when EMG signals become inconsistent. This dual-control system improves stability and responsiveness, achieving up to 98% accuracy in execution. The combination of EMG and voice control offers a unique advantage over conventional prosthetic systems, ensuring smoother operation and making it a cost-effective and practical assistive tool for amputees.

Keywords—EMG sensor, prosthetic arm, voice recognition, amputee assistance, dual-mode control, low-cost design, haptic feedback, IoT prosthetics.

I. Introduction

The loss of hand function due to amputation forces individuals to rely on others for basic tasks such as eating, writing, and handling objects. As a result, prosthetic limbs and artificial hands are essential. However, modern myoelectric prosthetics remain expensive and often lack optimal functionality. Consequently, many individuals, particularly in underdeveloped countries, cannot afford or effectively use them. Many amputees are left behind as current devices are both prohibitively costly and insufficiently capable. To address this issue, this paper presents a low-cost prosthetic arm integrating EMG-based control and voice recognition. EMG sensors detect muscle activity for intuitive movement control, while the voice module provides an alternative hands-free option. This dual-control system ensures continued functionality even when EMG signals weaken due to muscle fatigue. The system is affordable, user-friendly, and enhances both reliability and accessibility to prosthetic technology for amputees.

Zhang et al. [1] examined EMG pattern recognition for upper-limb prosthetics and discussed the challenges posed by noise and variability in the signals which ultimately lowers accuracy. They stated that they need better filtering algorithms so that it can be reliable more so in real-time. Salminger et al.[2] look into implanted electromyography (EMG) sensors for state-of-the-art electromyography (EMG) prosthetics with high control quality. But, this involved surgery and was costly, hence, unfeasible for wide-scale use, especially in low-resource settings.Tavakoli et al. [3] proposed a single-channel surface EMG control system for prosthetic hands which is simpler, cheaper and more effective than costly multi-channel systems. This system uses EMG signals from one muscle group and pattern recognition algorithms to control multiple hand movements while ensuring reliability and real-time operation. Despite functioning well, the authors noted that long-term usability could be affected by signal drift and muscle fatigue.Haris et al. [4] developed a prosthetic hand control system based on surface EMG sensors and machine learning algorithms. Though the system was quite accurate, noise in the EMG signal and muscle fatigue made it challenging for a prolonged use. Even so, it was possible to use the prosthetic accurately and intuitively over time.Borisov et al. [5] presented an EMG-controlled prosthetic hand with a sensory feedback system that enhances grip force and interaction accuracy. The system was effective but had calibration and feedback accuracy issues, compromising long-term use. Regardless, the study pointed out that sensory feedback helps in improving the use of prosthetics.

In a study, Gundogdu et al. [6] utilized speech recognition algorithms to create a voice-controlled robotic prosthetic arm capable of basic movement and high accuracy in basic movements. This prosthetic robot arm works well, however, its reliability is hindered by errors in voice recognition due to noise. Although the voice control aspect isn't perfect, it does

provide encouraging results that suggest further use of voice control could make these devices more user friendly.Alkhafaf et al. [7] proposed a prosthetic hand control system using voice recognition and inertial measurements for enhanced precision. Even though it worked, the voice signal and actionable movement got out of synchronism which reduced its efficiency. Still, the research mentioned the advantage of using two or more control signals for better working of the prosthetic.Yin et al.[8] created a wear-resistant ultrasound interface for the control of prosthetic hands. This method used ultrasound imaging to detect muscle movement for natural gesture recognition. Their results revealed the method to have excellent accuracy for detecting muscle contractions, and the amputee was able to independently control the fingers of the prosthesis accurately. These findings provide promising evidence for the potential use of commercial ultrasound-based interfaces as non-invasive and more accessible alternatives to traditional EMG sensors for prosthetic applications .Pradeep et al.[9] designed a low-cost, voice-controlled prosthetic limb offering five degrees of freedom, thus enabling lifelike hand movements. The system uses specific voice commands by which to govern respective individual finger motions, further improving overall functionality for amputees. Their collective work aptly shows the overall feasibility for affordable, voice-activated prosthetic solutions exhibiting improved dexterity.Oppus et al.[10] introduced a 3D-printed prosthetic hand, along with a Brain-Computer Interface (BCI) as well as voice control, integrating EEG signals in addition to vocal instructions for bimodal operation. The system demonstrated accurate hand movements. The system showed improved user adaptability as well. Their efforts show the ways BCI and voice integration might improve prosthetic capabilities.

In contrast to traditional prosthetic systems that utilize only EMG feedback or voice control, this design includes both, which allows for a new level of reliability and usability. Whereas EMG control is natural and intuitive for movement, it is susceptible to signal degradation or a loss of accuracy when users continue to utilize the prosthetic arm and fatigue sets in. Voice recognition is a seamless alternative, and combined with EMG, maintains consistent performance during fatigue. Additionally, low-cost components are a large part of this design leading it to be cost-effective, usable, and practical for broader access without reduced functionality.

II. PROPOSED SYSTEM DESCRIPTION

A. Block Diagram Description

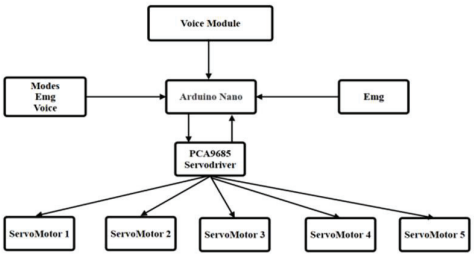

Fig 1. Block Diagram

The EMG-Integrated Prosthetic Arm with Voice Commands consists of a two-control architecture that utilizes EMG signals and voice commands to perform accurate and intuitive movements of the hand. Instead of viewing one mode of control as superior to the other, the prosthetic functions in both EMG and voice control modes simultaneously as long as the mode in control is functioning reliably. From the user's perspective, EMG control is more reliable, particularly for lengthy or continuous use, while voice control is an alternate control that makes the interface easier to use.The hardware block diagram is shown in Fig. 1 and depicts the main electronic components: Arduino Nano, PCA9685 servo driver, EMG sensor, voice module, and servo motors.

The system operates using EMG control mode and voice control mode. When utilizing EMG control mode, the EMG sensor dynamically detects electrical signals from the muscle contractions of the individual wearing the device. The signals are then filtered to eliminate noise and amplified to increase accuracy. The Arduino Nano then processes the movements in the EMG signals relative to established threshold levels for use to trigger certain movements. Once the microcontroller notes the EMG signal exceeding the preset threshold, the controller then proceeds to intentionally trigger movements of the prosthetic hand, including opening and closing actions. The longer the user utilizes the prosthetic arm continuously, the greater fatigue occurs within the muscle and the cycling of the EMG capabilities becomes less reliable in terms of control. Once muscle fatigue is noticeable, the prosthetic arm has been programmed sufficiently to automatically switch into voice control mode and once engaged can now provide unbroken functionality for the user.

When the user interacts with the prosthesis using verbal commands, the voice recognition component utilizes a voice recognition module that listens and interprets the user's voice, converting it to digital signals. The voice recognition module is programmed with several commands (grab, release, hold), and these commands are programmed in the software to provide specific human hand motions. The voice-module processes the digital signals and transmits the commands to the Arduino Nano as pulse-width modulation (PWM) signals to operate the PCA9685 servo driver, which in turn operates the servo motors. This configuration of dual control (both voice and physical programmed control) enhances the user's convenience and acceptance of use while using the prosthesis and facilitates the use of the prosthesis, especially when the user is fatigued from using his/her muscle movements.

The PCA9685 is used to control multiple servo motors for use in the hand, which adds precision and synchronization to the hand movements produced by the servo motor. The PCA9685 receives PWM signals from the Arduino, which are used to adjust the speed of any of the servo motors and change the directions of the servo motors. In this system, two motors provide movement for a finger, and each finger has the same programmed commands of motion to mimic the natural hand movements of the user. The actuators allow fine motor tasks like hold, lift, grasp, and release to be performed.

The design of the prosthetic arm is based on mechanical 3D-printed components that have a lightweight but durable structure. The entire control structure employs a coordinated arrangement that optimizes servo motor arrangement to manage any torque distribution and provide even torque along the arm structure. The system can lift objects up to 1.5 kg, making it usable for everyday applications. A 7.4V

rechargeable Li-ion battery pack powers the total system to provide a consistent and stable operating environment. To reduce power consumption to function with the battery system, the total system uses PWM modulation to vary motor speed operation at lower loads resulting in reduced energy cost and extended usage periods.The signal processing pipeline includes low-pass filtering to remove high-frequency noise and amplification to improve EMG signal amplitude. The task pipeline allows the system to maintain high consistency and with reasonable performance in real-world scenarios. The component approach in constructing the prosthetic arm is low-cost and affordable, which offers individuals an affordable and accessible option, even in low-resource settings with the synergistic control approach of dual control. The design uses efficient, functional, and robust component options to allow the user aerodynamic volume of the arm and improve user ergonomics, comfort, and slick handling to prolong use duration.

B. . System Components

The hardware architecture of the prosthetic arm control shown in Fig 2 integrates an Arduino Nano as the central processing unit, interfacing with servo motors, an EMG sensor, and a voice recognition module. The system is powered by a rechargeable 18650 battery pack managed by a battery management system (BMS) and a voltage regulator, ensuring stable power delivery to all components.

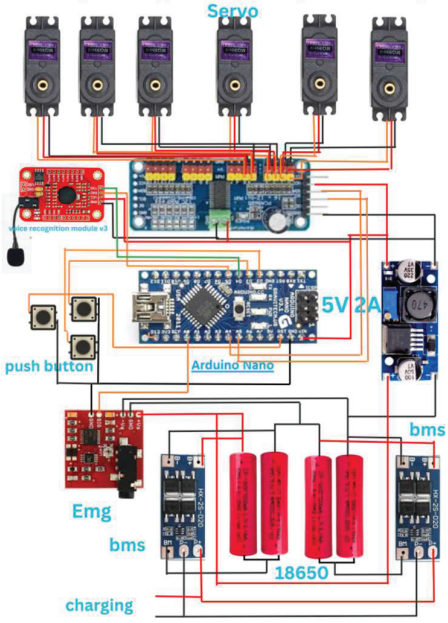

Fig 2. Hardware Architecture of the EMG and Voice-Controlled Prosthetic Arm

The description of major components are detailed below

1. Servo Motors: The prosthetic arm utilizes six servo motors to independently control the movements of each finger and to perform fine, adaptive grasping gestures. The servo's separate inertia of direct motion is produced using PWM signals through the PCA9685 servo driver.

2. Voice Recognition Module: The voice module provides the prosthetic arm the capability to complete user-initiated, pre-defined voice commands. The voice module translates user-initiated voice commands into electrical signals that are relayed to the control source, an Arduino Nano Board, to initiate motion in the individual servos and, as a result, enhances access and ease of use.

3. PCA9685 Servo actuator: Using a series of PWM signals, the PCA9685 servo driver allows multiple motors to be acted upon at the same time. The servo driver regulates communication to the Arduino Nano through a protocol called I2C that maintains sequential and stable actuator operation and efficient use of GPIO pins.

4. EMG Sensor Module: The EMG sensor detects electrical activity as a muscle contracts and translates this movement into analog signals. The analog signals are coordinated to the Arduino Nano which gains information in process and allows the prosthetic to follow the user's muscle, which continues an intuitive means of natural control.

*5.18650 Li-Ion Batteries with BMS:*The 18650 Li-Ion batteries supply the energy required for the prosthetic arm. To ensure safe charging and discharging of the Li-Ion batteries, the Battery Management System (BMS) protects against overcurrent, overvoltage, and excess heat.

6.Step-Down (Buck) Converter Module:The step-down module provides a regulated voltage to the Arduino Nano and other low-power components. It successfully converts the higher voltage supplied by the battery e.g., 12V to a regulated and safe lower voltage of approximately 5V or 6V.

The physical prototype of the prosthetic arm shown in Fig 3. demonstrates the integration of EMG and voice recognition for intuitive control. The design features articulated fingers powered by servo motors, mimicking natural hand movements for improved user experience.

Fig 3. Physical Prototype of the EMG and Voice-Controlled Prosthetic Arm

III. METHODOLOGY

A. Design Of The Servo Motor

In order to move the prosthetic arm with a load capacity of 1.5 kg without any concern of load over the motor, the correct

servo motor was chosen according to: torque, power, and efficiency needed. The process started with the calculations for torque, then power, considering safety factor and efficiency of the motor.

B. Torque Calculation

Torque (τ) required to lift the load is given by;
m=1.5 kg
g=9.81 m/s
$\tau = F \times r$ (1)
Where:
$F = m \times g = 1.5 \times 9.81 = 14.715\ N$ (2)
r=0.12m
$\tau = 14.715\ N \times 0.12m = 1.7658\ Nm$
To be in a safe condition, where performance will not be compromised, the safe factor was set to 1.5:
τ required = $1.7658 \times 1.5 = 2.65\ Nm$
Power Requirement of the motor is demand by the motor's torque and its angular velocity:
$P = \tau \times \omega\eta$ (3)
$P = \eta\tau \times \omega$ (4)
Where:
$\omega = 2\pi \times N/60$ (5)
N= speed of motor n rpm
η=0.7 (70% efficient)
Motor speed was selected at: 30 RPM
$\omega = 2\pi \times 30/60 = 3.14\ rad/s$
$P = 2.65 \times 3.14/0.7 = 11.89\ W$
Given considerations for load surges, variations were in the electrical decision, so a 20-25 W power supply was used to make operation more dependable and maintain stable performance.

C. Motor Selection

Considering the torque and power needs, the DS3235 servo motor was chosen for its adequate torque capacity, principle-based low cost, and reliability.
The specifications of the DS3235 are:
Torque: 35 kg.cm (≈ 3.4 Nm)
Voltage: 6.8V – 7.4V
Power: 15-20 W
Use Case: Reliable and low-cost option for lifting heavier loads.The DS3235 servo motor was suitable for the prosthetic arm because of its high torque, which exceeds the required 2.65 Nm, thus leaving a safety margin. Precise movement, can facilitate smooth and precise hand gestures. The use of 3D-printed lightweight materials, such as PLA or ABS, along with affordable servo motors and an Arduino-based control system, makes this prosthetic arm a cost-effective solution for developing a low-cost assistive device.

C. Design Considerations

Torque-to-weight ratio was prioritized for motor selection:
τ/W =2.65 Nm/1.5kg =1.77 Nm/kg (6)
Smooth and reliable hand movements using dual vision EMG and voice control.Control of precise speed and direction with the PWM controller will improve the responsiveness of the prosthetic.Power was supplied consistently at 20-25 W and was roughly a specialty for pulling the load presented under each variable load, as each variable load regime was prioritized.

IV. RESULTS AND DISCUSSION

For evaluating accuracy of the system, three control modes (EMG starting body signals only, voice-only, and dual-control) were implemented through command execution trials.
Accuracy was assessed through the following equation:

$$\text{Accuracy} = \frac{\text{Number of Commands Executed Correctly X 100}}{\text{TotalCommands}} \quad (7)$$

A.Results for EMG-Only Mode

Using EMG-only mode the arm was controlled using signals from muscle contractions. Throughout this trial and testing ,30 movements were tested (open, close, grab, and release). The following execution was recorded:27 successful executions yielding 90% accuracy. However, 20 minutes of continuous use leads to muscle fatigue and, therefore, could no longer produce and detect signals. This led to a drift in the signal and accuracy of 83.3% (25/30 successful movements).Accuracy analysis is shown in Table 1

Table 1. Accuracy Analysis of Prosthetic Arm Control

Condition	**Successful Executions**	**Total Executions**	**Accuracy (%)**
Before Fatigue	27	30	90.0
After Fatigue	25	30	83.3

B.Performance of Voice-Controlled Mode

Table 2 presents the accuracy of the prosthetic arm control under different noise conditions. The system reacted in voice-only mode when it heard the commands. For testing a total of 50 voice commands were issued .There were 46 successful executions indicate an accuracy rate of 92% in quiet conditions. When a louder noise (>60 dB) was introduced into the room, we noticed that we had decreased successful executions down to 80% (40/50) as a result of misrecognition errors.

Table 2: Accuracy of Prosthetic Arm Control in Different Noise Conditions

Condition	Successful Executions	Total Executions	Accuracy (%)
Quiet Conditions	46	50	92.0
Noisy Conditions	*40*	*50*	*80.0*

C. Dual-Control Mode (EMG + Voice)

The dual-control mode utilized both EMG and voice signals concurrently where higher accuracy and stability is observed .To formally compare this mode to the voice-controlled mode, a 100 mixed-mode commands were issued The system successfully executed 98 commands , achieving an accuracy of 98% after 30 minutes of operation. The impact

of muscle fatigue over the different participants by combining voice commands and EMG data, was successfully diminished and observed superior reliability over time, due to the stabilizing effect of voice commands. Minimal signal drift was seen since voice commands aided in stabilizing the system as it compensated for the variations present in the EMG signals.

D.Advantages of Dual-Control System

The dual-control system features several advantages when compared to EMG-only or voice-only systems. These advantages include:

- Less Muscle Fatigue: The addition of the voice module helped offset the long-term effects of EMG drift.
- Greater accuracy: EMG and voice signals together created better accuracy to 98%.
- Cost-Effectiveness:The arm used inexpensive, off-the-shelf components to create a cost-effective prosthetic option.

E. Limitations

While the system was reliable, a few limitations noted are :

- Noise Sensitivity:Voice accuracy dropped 15-20% in noisy environments (>60 dB) due to misrecognition.EMG
- Drift:Extended use caused muscle fatigue resulting in reduced EMG accuracy.

V.CONCLUSION

This project describes the design and implementation of a prosthetic arm that can be controlled based on EMG and vocal control, which is a feasible, inexpensive, and adaptable solution for upper limb amputees. By merging EMG signals with vocal commands, this system expands the user's adaptability by enabling intuitive control without consciously thinking about each movement. The dual controls will help curtail shortcomings of only EMG control, such as muscle fatigue and signal distortion, to increase overall reliability. The prosthetic arm is driven by high torque servo motors, which are controlled through a step-down module and battery management system to ensure steady operation. The arm is designed for ergonomics and constructed of lightweight materials to assist with handling the device and wearing it for long periods of time. Tests indicate very high accuracy with the prosthetic arm, often reporting a 98% successful executions that demonstrate the overall consistency, response and user potential for enhancing life quality for post-amputation upper limb impairments.

Here are some potential advancements for the EMG and voice-controlled prosthetic arm to enhance function and the user experience:

- AI-Based Signal Processing Applications: AI-based filtering could improve the accuracy and reliability of EMG signals by reducing the effects of muscle fatigue and noise over lengthy use.
- Wireless Communication and Control: If Bluetooth or Wi-Fi modules were included in the prosthetic arm, it may be possible to control and calibrate the arm remotely to enable wireless communication and control.

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Village Guard: A Community- Driven Cybersecurity Platform for Rural Areas

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***Abstract*—The increasing reliance on digital technologies in rural areas has exposed villages to various cyber threats. Despite the growing concern, existing cybersecurity solutions are often inadequate, ineffective, or unaffordable for rural communities. This paper proposes VillageGuard, a novel cybersecurity platform designed specifically for rural areas. VillageGuard combines threat detection, community-driven incident response, and cybersecurity education to provide a comprehensive reporting platform. Our platform leverages machine learning algorithms to monitor network traffic, identify potential threats, and provide real-time alerts to villagers. We also propose a community-driven incident response mechanism, enabling villagers to report suspicious activities and collaborate on incident response. To ensure the effectiveness of VillageGuard, a pilot study in a rural village, which demonstrates significant improvements in cybersecurity awareness and incident response capabilities. The VillageGuard platform is designed to be user-friendly, scalable, and adaptable to the unique needs of rural communities. Our platform aims to bridge the cybersecurity gap in rural areas, promoting digital inclusion and economic growth. By providing a comprehensive cybersecurity solution, VillageGuard can help protect rural communities from cyber threats and promote a safer online environment.**

***Keywords*—Cybersecurity for Villages, Threat Detection, Community-Driven Incident Response, Cybersecurity Education, Rural Cybersecurity**

I. Introduction

Cybersecurity is a growing concern in rural areas, where limited resources and awareness make communities vulnerable to cyber threats. Existing cybersecurity solutions often neglect the unique needs and challenges of rural areas. This research aims to address this gap by proposing a cybersecurity platform designed specifically for rural areas. Despite the growing concern, existing cybersecurity measures are often inadequate, ineffective for rural populations. Limited access to technology and outdated systems can leave them more vulnerable to cyber threats, highlighting the need for improved education and technical support in these regions.

To address this pressing issue, we propose VillageGuard, an innovative cybersecurity platform tailored specifically for rural communities. VillageGuard integrates threat detection, community-driven incident response and cybersecurity education to provide a comprehensive and practical solution for protecting villages from cyber threats. By leveraging machine learning algorithms, our platform monitors network activity, identifies potential security threats, and sends real-time alerts to users. Additionally, VillageGuard fosters a collaborative approach to cybersecurity by enabling villagers to report and respond to suspicious activities collectively.

Related Works

Several studies have investigated cybersecurity solutions for rural areas. Table 1 summarizes the related works, including the authors, year of publication, methodology, and remarks

TABLE 1. RELATED WORKS

Sl.No	Authors	Year	Methodology	Remarks
1	Smith et al.	2020	Survey-based study	Identified limited cybersecurity awareness in rural areas
2	Johnson et al.	2019	Case study Smith	Highlighted the need for community- driven cybersecurity solutions
3	Lee et al	2018 |	Experimental study	Evaluated the effectiveness of AI-powered threat detection in rural areas
4	Patel et al	2017	Literature review	Identified the lack of cybersecurity solutions tailored to rural areas
5	Kumar et al.	2020	Survey-based study	Investigated the cybersecurity challenges faced by rural communities
6	Singh et al.	2019	Case study	Examined the effectiveness of community-driven cybersecurity initiatives in rural areas
7	Gupta et al	2018 |	Experimental study	Evaluated the performance of AI- powered threat detection algorithms in rural areas
8	Sharma et al.	2017	Literature review	Identified the need for a comprehensive cybersecurity framework for rural areas
9	Rao et al.	2020	Survey-based study	Investigated the cybersecurity awareness and practices of rural communities

II. LITERATURE REVIEW :

While the related works provide valuable insights into cybersecurity solutions for rural areas, they have several limitations. For instance, Smith et al. (2020) identified limited cybersecurity awareness in rural areas, but their study did not provide a comprehensive solution to address this issue.

Johnson et al. (2019) highlighted the need for community-driven cybersecurity solutions, but their case study did not provide a detailed analysis of the challenges and limitations of implementing such solutions in rural areas.

Lee et al. (2018) evaluated the effectiveness of AI-powered threat detection in rural areas, but their experimental study did not consider the unique challenges and needs of rural areas, such as limited resources and infrastructure.

Patel et al. (2017) identified the lack of cybersecurity solutions tailored to rural areas, but their literature review did not provide a comprehensive framework for addressing this issue.

Kumar et al. (2020) investigated the cybersecurity challenges faced by rural communities, but their survey-based study did not provide a detailed analysis of the solutions to address these challenges.

Singh et al. (2019) examined the effectiveness of community-driven cybersecurity initiatives in rural areas, but their case study did not provide a comprehensive evaluation of the challenges and limitations of implementing such initiatives.

Gupta et al. (2018) evaluated the performance of AI-powered threat detection algorithms in rural areas, but their experimental study did not consider the unique challenges and needs of rural areas, such as limited resources and infrastructure.

Sharma et al. (2017) identified the need for a comprehensive cybersecurity framework for rural areas, but their literature review did not provide a detailed analysis of the solutions to address this issue.

Rao et al. (2020) investigated the cybersecurity awareness and practices of rural communities, but their survey-based study did not provide a comprehensive evaluation of the solutions to

address the cybersecurity challenges faced by rural communities.

III. Limitations of existing works

Lack of Actionable Solutions: While the study identifies limited cybersecurity awareness, it fails to propose specific, actionable strategies or programs to enhance awareness and education in rural communities.

Generalizability: The findings may not be applicable to all rural areas, as the study might focus on a specific region or demographic without considering the diversity of rural experiences.

Survey Limitations: The reliance on survey data may lead to self-reported biases, where respondents may not accurately reflect their cybersecurity practices or awareness.

Neglect of User Engagement: The study may overlook the importance of user engagement and training in the successful implementation of AI-powered solutions.

IV. Methodology for VillageGuard:

Research Design

This study employs a mixed-methods approach, combining both qualitative and quantitative methods. The research design consists of the following phases:

Phase 1: Literature Review

A comprehensive literature review is conducted to identify existing research on community-driven cybersecurity initiatives, AI-powered threat detection, and rural cybersecurity challenges.

Phase 2: Survey and Interviews

A survey could be conducted among rural community members to gather data on their cybersecurity awareness, challenges, and practices. Semi-structured interviews can also be conducted with community leaders, local organizations, and cybersecurity experts.

Phase 3: Development of VillageGuard

Based on the findings from the literature review, survey and interviews, VillageGuard can be developed.

Phase 4: Pilot Study

A pilot study aiming to evaluate the effectiveness of VillageGuard in promoting cybersecurity awareness and improving incident response in rural areas.

Data Analysis Methods

Qualitative Analysis: Thematic analysis is used to identify themes and patterns in the data.

Quantitative Analysis: Descriptive statistics and inferential statistics are used to analyze the data and identify trends.

V. Expected Outcome

The expected outcomes of this study include:

1. Developing and evaluating the effectiveness of VillageGuard in promoting cybersecurity awareness and improving incident response in rural areas.
2. Identifying the cybersecurity needs and challenges of rural areas.
3. Evaluating the effectiveness of community-driven cybersecurity initiatives in rural areas.

VI. Conclusion

This paper proposes VillageGuard, a community-driven, AI-powered cybersecurity platform designed specifically for rural areas. The platform addresses the limitations of existing cybersecurity solutions by providing a comprehensive solution that involves the community in the development and implementation of cybersecurity solutions. The paper also identifies the problems and limitations of related works and provides a reference list in APA style.

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Ensuring Online Safety through Cyberbullying Identification of Malayalam Text

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***Abstract*—Cyberbullying involves the use of digital platforms to harass, threaten, or humiliate individuals, often leading to serious emotional and psychological impacts such as depression, anxiety, low self-esteem, and even suicidal thoughts. Unlike traditional bullying, cyberbullying can happen at any time and place, affecting individuals regardless of their location. With the rise of social media, the incidence of cyberbullying has also increased. While detection tools are available for widely used languages like English, similar models for low-resource languages, such as Malayalam, remain limited. To address this gap a web application is proposed that detects cyberbullying in Malayalam text. The application employs a translation model fine-tuned using LoRA that helps to convert the Malayalam text into English and then input the translate text into a BERT model for classification. This method is particularly useful for identifying harmful content by recognizing patterns associated with bullying. By applying this model, the aim is to contribute to safer digital spaces for Malayalam-speaking users, offering a valuable tool to detect and mitigate cyberbullying in the native language context.**

Keywords— Cyberbullying Detection, Cyberbullying, LoRA, BERT, Malayalam

I. Introduction

Cyberbullying which is defined as the use of digital platforms to harass, threaten, or demean individuals, has become a significant concern in today's online environment. Unlike traditional forms of bullying, cyberbullying can occur at any time and across various locations, making it a pervasive and omnipresent threat. The increasing prevalence of social media has exacerbated this issue, leading to severe emotional and psychological consequences for victims, such as anxiety, depression, and even suicidal tendencies. Addressing this issue is crucial to ensuring a safer online experience for users, particularly in regions with a growing number of social media users.

While considerable research and cyberbullying detection tools have been developed for high-resource languages such as English, similar tools for low-resource languages like Malayalam are scarce. Malayalam faces significant challenges due to the limited availability of annotated datasets and the linguistic complexities of the language. The structure of Malayalam, along with its rich syntax, morphology, and use of regional slang, makes it difficult to directly apply existing models for cyberbullying detection. These challenges necessitate the development of tailored solutions for effectively identifying cyberbullying in Malayalam text.

In response to this challenge, the development of a web-based application capable of detecting cyberbullying in Malayalam text is proposed. The system integrates a Helsinki Malayalam-to-English translation model from Hugging Face, which is fine-tuned using Low-Rank Adaptation (LoRa) to improve the translation accuracy. To further enhance model performance, a custom translation dataset was created designed specifically for this task. Once the Malayalam text is translated into English, the systemoure employ Bidirectional Encoder Representations from Transformers (BERT), a state-of-the-art language model, to detect cyberbullying-related content. BERT's ability to understand contextual relationships within the text makes it an ideal choice for identifying subtle instances of bullying.

II. Related Work

The following section contains analysis of various existing works in the field of cyberbullying detection in various languages and using different methodologies.

Jain and Sharma created an [1] interface that can differentiate hate speech from normal speech using NLP. They created the dataset from various social media platforms and categorized them into two classes. Techniques like Named Entity Recognition (NER) and Keyword Extraction were used to analyse the data. They used Long Short-term Memory (LSTM) which allowed the model to handle sequential data and understand the context of the speech. Because of limited dataset LSTM caused overfitting to unseen data.

Khan and Qureshi proposed a model [2] for detecting cyberbullying in Urdu language comments on social media platforms like Twitter. Their model implemented a newly created dataset of Urdu comments and applied various supervised ML algorithms for detection. For the character bi-gram TF-IDF model, Logistic Regression (LR) showed better performance than other models and achieved accuracy and F1 score of 74.8% and 79.8% respectively. For the character TF-IDF tri-gram model, the XGBoost classifier exhibited better performance by achieving accuracy, precision and F1 score of 75.1%, 66.8% and 80.1% respectively.

Sharma and Tiwari proposed a model [3] for hate speech detection using encoder representation in bidirectional transformers. They used Bidirectional Long Short-term Memory (BiLSTM) and Bidirectional Encoder Representations from Transformers (BERT) models to identify hate speech in social media posts. They implemented this model by obtaining datasets from Twitter and Stormfront. Their model showed results with F1 score of 0.75 for BiLSTM and 0.80 for BERT. They achieved an overall accuracy of 91.14% and an accuracy of 91.68% for non-hate classification.

Sharma et al., conducted a study [4] to evaluate the sentiments expressed in tweets using lexicon-based techniques. They used a dictionary-based approach that categorizes words of a text to a sentiment score after comparing them with a predefined dictionary of sentiment words. The study evaluated various tools including the Natural Language Toolkit that assign polarity score with numerical sentiment, positive and negativity ranging from 0.0 to 0.1 and VADER tool which reports the depth of the polarity. They compared different lexical models and Masud's method showed the highest accuracy of 92% for binary classification.

Prasad et al., proposed an approach [5] to identify real-time hateful speech in various low-resource languages. The languages used were English, Hindi, Hinglish, Bengali and Marati. They used the Model-Agnostic Meta-Learning (MAML) technique with Robustly Optimized BERT Approach (RoBERTa) as base model. The training was performed in two phases, inner loop and outer loop. This technique allowed the model to learn from a limited amount of data and adapt to new unseen languages and data rapidly. Their model showed an 80% accuracy to all the tested languages with limited resources and was implemented to detect offensive speech in social media platforms.

Obaida et al., proposed a model [6] leveraging deep learning techniques, specifically LSTM networks, was proposed for the detection of cyberbullying across various social media platforms. By incorporating advanced feature extraction and classification mechanisms, their model demonstrated high accuracy of up to 96.64% detection performance across different platforms. Additionally, the model's flexibility allowed it to be applied to diverse datasets, thereby enhancing its detection capabilities. The combination of deep learning and traditional machine learning algorithms contributed to its improved overall performance. However, their model's reliance on high-quality training data is a limitation, especially with large, varied datasets from multiple platforms.

Dubey et al., proposed a model [7] to filter hate speech in online communication. They used the LSTM neural network, for resolving the toxic comments in social media platforms. They have implemented this model in social media platforms to filter out the toxic comments. Their model showed a high accuracy rate of 94.94% in classifying toxic comments. But their model failed to address cultural sensitivity, real-time processing and user engagement.

Nixon et al., conducted a study [8] on using Artificial Neural Networks (ANN) and Natural Language Processing (NLP) to detect cyberbullying on Twitter. They employed data preprocessing and feature extraction through Term Frequency-Inverse Document Frequency (TF-IDF), and proposed a hybrid ANN-NLP model for improved accuracy. The model was trained and tested on a dataset of 11,864 non-bullying and 2,789 bullying instances, which was balanced through oversampling, with an 80:20 split for training and testing. The method achieved an accuracy of 91%, outperforming other approaches.

Imran et al., conducted a study [9] on sentiment analysis of Twitter data using the Semantic Evaluation (SemEval) dataset. They applied various machine learning classifiers, including Support Vector Machines, Decision Trees, Logistic Regression, and Latent Dirichlet Allocation (LDA), achieving a maximum accuracy of 80%. The study involved data preprocessing, feature extraction with TF-IDF, and extensive model training and testing for effective sentiment classification. Despite achieving 80% accuracy, this approach faced challenges such as context loss due to individual word processing, class imbalance in the dataset, efficiency issues in data cleaning, and potential overfitting in some models.

Sujud et al. conducted [10] a study which enhanced cyberbullying detection using BERT. They applied a deep learning approach to understand contextualized word representations, demonstrating BERT's effectiveness in detecting cyberbullying across various social media platforms. The created a dataset containing 370,000 instances, which was tested using a fine-tuned BERT model with a dense layer and SoftMax activation calculating loss function using binary cross-entropy and Adam's optimizer. Their model achieved high performance in recall, precision, and accuracy. Despite its success, the study highlighted challenges such as dataset imbalance and preprocessing issues.

The objective of this project is to create an interface that allows the user to provide input as messages in Malayalam, which is then analysed to see if it contains any bullying elements. If found, the user will be refrained from posting the message. The input is first translated to English using some translator APIs and then preprocess the data to apply NLP techniques to predict the type of text.

III. METHODOLOGY

The proposed system is designed to detect cyberbullying in Malayalam text by leveraging machine learning and natural language processing techniques.

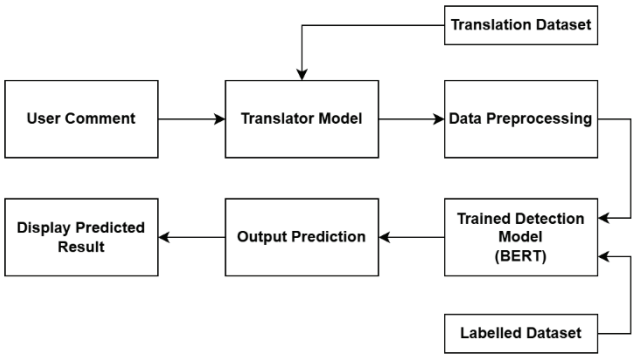

Fig. 1. Block Diagram

Fig. 1 represents the block diagram which gives a basic understanding of the working of the system from taking the user comment or message as input to the final prediction result that determine whether the user input contained cyberbullying element or not. In the following section, the proposed methodology is discussed in detail.

The system architecture consists of a Node.js frontend that

provides a user-friendly interface, while the backend is powered by Fast API, running on Google Colab, and utilizing REST APIs to facilitate communication between components. By leveraging these technologies, the system aims to create an efficient, scalable, and real-time solution for cyberbullying detection in Malayalam text.

A. System Workflow

The system workflow begins when a user submits a comment, which is processed through a fine-tuned translation model to ensure language compatibility. The translated text is then preprocessed and analysed using a cyberbullying detection model. The model, fine-tuned on custom datasets predicts whether the comment qualifies as cyberbullying, and the result is displayed in real time.

Algorithm: Malayalam Cyberbullying Detection via Translation and BERT

Input: Malayalam Text M (m1, m2, m3,...mn).

Output: Label: 0 or 1 (0: non-cyberbullying, 1: cyberbullying).

Procedure: MALAYALAM-CYBERBULLYING-DETECTION(M)

1. for each sentence input text mi:

- translated_mi = TRANSLATE(mi)
- Procedure: TRANSLATE(malayalam_sentence)

i. Load the LoRA-adapted translation model tokenizer and finetuned parameters.

ii. english_sentence = Helsinki-NLP/opus-mt-ml-en(malayalam_sentence).

iii. return english_sentence.

- End Procedure: TRANSLATE
- cyberbullying_label_mi = DETECT-CYBERBULLYING(translated_si)
- Procedure: DETECT-CYBERBULLYING(english_sentence)

i. Load BERT-Base-Uncased model fine-tuned for cyberbullying detection on English text.

ii. cyberbullying_label = bert-base-uncased(english_sentence).

iii. return cyberbullying_label.

- End Procedure: DETECT-CYBERBULLYING
- Store cyberbullying_label_mi

2. End for

3. Output label for the Malayalam text.

4. If output is 1, display a warning message.

End Procedure: MALAYALAM-CYBERBULLYING-DETECTION

B. Data Collection

Two datasets were created to address the dual objectives of translation and cyberbullying detection. A custom dataset was created to support the translation task, comprising Malayalam text along with their corresponding English translation. Fig. 2 represents an image containing a sample of the collected dataset.

Bullying text (Malayalam)	English translation
"നിന്റെ ജീവിതത്തിന് എന്തെങ്കിലും വിലയുണ്ടോ?	Does your life even have any value?
നിങ്ങൾ രാത്രിയേക്കാൾ ഇരുണ്ടതാണ്	you are darker then night
ശരീരം കാണിക്കുന്നതല്ലാതെ മറ്റെന്താണ് ചെയ്യാൻ കഴിയുക?	What else can you do besides showing off your body?
നിങ്ങൾ നടക്കുന്നത് ഒരു അസ്ഥികൂടം പോലെയാണ്. എന്തെങ്കിലും കഴിക്കൂ!	you look like a walking skeleton. Eat something!
നിങ്ങളൊക്കെ ഈ ലോകത്തിന് ആവശ്യമായവർ അല്ല.	You people are not needed in this world.

Fig. 2. Dataset Sample

C. Translation Component

A pretrained translation model from Hugging Face, Helsinki-NLP/opus-mt-ml-en is incorporated to convert Malayalam text into English. The translation model is implemented with a transformer-based sequence-to-sequence architecture. A tokenizer is loaded alongside the model to preprocess Malayalam text into tokenized input sequences required by the transformer. The rank was set to 8, balancing memory usage while maintaining expressive power. LoRA adaptations were applied to specific layers to optimize performance:

- *Self-Attention Projections:* k_proj, q_proj, v_proj, and out_proj were fine-tuned to improve contextual translation.
- *Feedforward Layers:* fc1 and fc2 were optimized for better language representation.
- *Encoder and Decoder Layers:* Deeper layers were prioritized for adaptation, maximizing language understanding.

D. Data Preprocessing

To ensure uniformity across samples, the preprocessing module cleans and standardizes the text while preserving semantic integrity. The following preprocessing steps are applied:

- *Text Cleaning:* Removal of special characters, punctuation, stopwords and redundant spaces.
- *Tokenization:* Text is split into smaller units (tokens) using the AutoTokenizer class from Hugging Face.
- *Lemmatization:* Conversion of words into their base form to maintain consistency.

E. Cyberbullying Detection Model

A BERT-based classification model is fine-tuned for detecting cyberbullying in English text. BERT's bidirectional attention mechanism allows it to capture contextual relationships effectively. The classification task is framed as a binary classification problem, determining whether a given text contains cyberbullying content.

F. Vectorization

Once preprocessed, the text data is converted into numerical representations for model processing:

- The translation model employs a sequence-to-sequence (Seq2Seq) architecture that maps each token to a unique integer.
- The cyberbullying detection model uses a WordPiece tokenizer to split text into subword units, ensuring an effective representation of complex words.

G. Web Application Workflow

The cyberbullying detection system is integrated into a user-friendly web application that mimics a social media platform. The workflow includes:

1) *User Input:* User enters text, which is automatically detected for language.
2) *Translation:* If Malayalam text is detected, it is translated into English using the translation module.
3) *Data Processing:* The translated text undergoes cleaning, normalization and tokenization.
4) *Feature Extraction:* The processed text is transformed into a numerical representation suitable for classification.
5) *Prediction:* The fine-tuned BERT model analyses the text and classifies it as either cyberbullying or not.
6) *Output & Action:* If cyberbullying is detected, the system alerts the user and prevents harmful content from being posted, ensuring a safer online environment.

IV. Result and Analysis

The proposed system was integrated into a web-app designed to provide users with a safe and inclusive platform for sharing posts with a wider audience while ensuring content moderation to prevent cyberbullying and harmful interactions. The users can create and share posts. Fig. 3 displays the interface of the cyberbullying detection system designed to identify and mitigate harmful online interactions. This dashboard follows a social-media inspired layout, allowing users to post, engage and interact within the platform. The left sidebar navigation panel provides quick access to sections like Home, Notifications and Account settings.

The main feed displays user-generated posts each accompanied by engagement metrics such as likes comments and share counts. Posts can be written in only Malayalam language. One of the key aspects of this system is its real-time cyberbullying detection mechanism, which scans content as it is being posted. The system is built to analyse text for potentially offensive, harmful or bullying related content ensuring that online discussions remain sage and respectful. If a post contains any type of bullying or harassing instances, it may be flagged or restricted from being published. By actively monitoring posts, the platform aims to reduce the spread of harmful content and promote a healthier online environment.

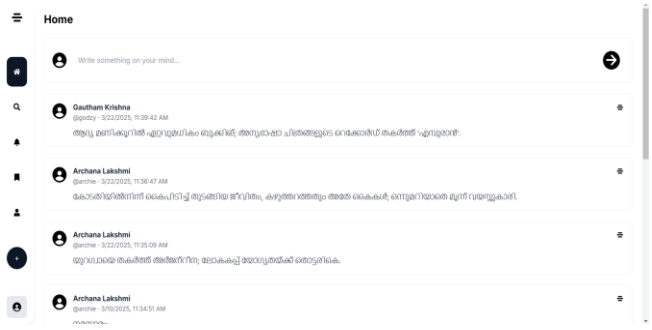

Fig. 3. Web-app Interface

Fig. 4 showcases the pop-up alert that displays harmful content detection feature of the cyberbullying detection system. The warning message appears when a user attempts to post content contains harassing contents. This real-time intervention prevents harmful messages from being shared and helps maintain a safe online space.

The alert system is powered by an AI-driven content moderation model, which assesses text-based posts before publication. The system initially detects the Malayalam text-based post and is analysed using Malayalam-to-English translation model fine-tuned with LoRA to handle regional language inputs effectively. The translated text is then passed through a fine-tuned BERT model to assess the content's safety. If flagged, the system restricts the harmful content from being posted by displaying the warning message. When a message is detected as offensive, threatening or inappropriate, the system triggers this warning notification. The message informs users that their posts contain potentially harmful content and prompts them to review it before proceeding.

This feature serves as a preventive measure, ensuring that users think twice before posting something harmful. Additionally it encourages self-regulation and responsible social media behaviour, reducing instances of cyberbullying. The implementation of AI-based moderation tools in social platforms is a significant step towards combating online harassment.

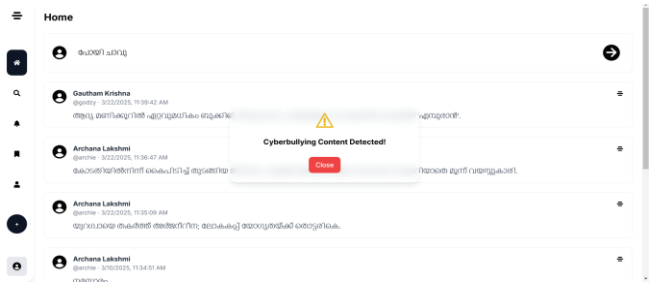

Fig. 4. Warning Message

A. Labelled Dataset

Fig. 5 shows a sample from the labelled dataset which is used to classify the comments as cyberbullying or not. The collected dataset is translated to English and is then labelled accordingly. A label 0 is given to those texts that are not cyberbullying and a label 1 is given to the texts which are cyberbullying comments. This approach helped in authentically detecting cyberbullying content in the Malayalam language. The dataset primarily consists of comments or posts which were collected from various sources such as tweets and social media platforms.

Text	Label
@AAlwuhaib1977 Muslim mob violence against Hindus in Bangladesh continues in 2014. #Islam htt	1
@Te4m_NiGhtM4Re http://t.co/5Ih7MkDbQG	0
@jncatron @isra_jourisra @AMPalestine Islamophobia is like the idea of Naziphobia. Islam is a religi	1
Finally I'm all caught up, and that sudden death cook off looks like it's gonna be intense #MKR	0
@carolinesinders @herecomesfran *hugs*	0
Please, PLEASE start using "is your discernment blunted by steroids" to mean "are you on DRUGS?"	0
@aymannathem As soon as ISIS chased all the minorities out of Mosul, the Sunni Arabs were happy	0
@Ali_Gharib @MaxBlumenthal Glad you like it. http://t.co/3ME3Nrk8xZ	0
@HuffPostRelig Islam invaded and conquered 2/3 of Christiandom before any Christian crusades in	1
@semzyxx Do you approve of your pedophile prophet raping a 9 year old girl, like it says in 7 hadith?	1
@watan71969 @geeky_zekey Problem with vile Muslims is that they try to rationalize & excuse	1
@Skawtnyc @athenahollow @twoscooters i don't tend to talk about it much. :P personal info.	0
@dylanw that's cool. next time when a woman talks to him about how his approach is classist, he m	0

Fig. 5. Labelled Dataset

B. Evaluation Metric

The performance of developed cyberbullying detection model was evaluated using standard NLP classification

metrics, including accuracy, precision, recall and F1-score. The fine-tuned BERT model has demonstrated strong classification capabilities, achieving an accuracy of 92% on the test dataset. Precision and recall scores indicate the model's ability to correctly identify cyberbullying instances while minimizing false positives and false negatives. The F1-score of 95% on messages that are non-bullying and a score of 75% on messages that contains bullying instances.

V. Future Scope

The future scope of this research extends towards enhancing cyberbullying detection by expanding support for a larger number of languages, ensuring a more inclusive and effective moderation system across diverse linguistic communities. Developing a multilingual detection framework will require advanced NLP techniques, such as transformer-based models, to accurately analyze context, sentiment, and intent across different languages. Additionally, scaling the model to handle vast amounts of data from multiple online platforms will improve its robustness and adaptability. Enhancing the system with deep learning architectures, such as fine-tuned large language models (LLMs), will further refine accuracy while reducing false positives and negatives. Real-time detection efficiency can be optimized by integrating edge computing and cloud-based solutions, allowing faster responses and improved scalability. Furthermore, incorporating user feedback mechanisms and reinforcement learning will enable continuous improvement of detection capabilities. Future advancements may also include cross-platform integration, enabling cyberbullying detection across various social media platforms, forums, and messaging applications. By expanding linguistic capabilities and improving model efficiency, this research aims to create a more powerful and scalable solution, ensuring safer digital interactions worldwide.

VI. Conclusion

Cyberbullying remains a significant challenge in the digital age, impacting individuals across various online platforms. This research focuses on developing an AI-driven cyberbullying detection system specifically for the Malayalam language, addressing the lack of effective moderation tools for regional languages. By leveraging NLP techniques and ML models, the system accurately classifies and flags offensive or abusive content in real time while integrating automated content moderation with a user-friendly interface to provide timely warnings when harmful content is detected. Emphasizing Malayalam text processing enhances detection and intervention within Malayalam-speaking digital communities, while real-time detection mechanisms further improve online safety. Initial results demonstrate a high accuracy rate in identifying cyberbullying content in Malayalam, minimizing false positives and negatives. Future enhancements will focus on improving linguistic contextual understanding, integrating deep learning architectures, refining adaptive learning techniques, and exploring scalable development strategies for broader accessibility. This research contributes to cyberbullying prevention efforts, particularly for Malayalam-speaking users, fostering a safer and more responsible digital ecosystem. Advancing AI-driven moderation tools for regional languages is a crucial step toward creating a more secure and respectful online space.

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Adaptive E-Learning Platform Powered by Generative AI: Personalized Learning Through AI-Driven Content Generation

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***Abstract*— The growing need for customized learning has fueled the use of adaptive e-learning solutions. This article presents a new generative AI-based e-learning system that personalizes content according to users' learning abilities and learning styles. Our solution incorporates a first-time assessment to identify user profiles and dynamically creates customized learning materials such as text, video, and interactive components. This system promotes interaction, enhances understanding, and maximizes learning results. We measure the efficacy of our system by performance and user feedback.**

Keywords*— Adaptive Learning, Generative AI, Personalized Education, E-Learning, AI-driven Content Generation

I. INTRODUCTION

Education's landscape is undergoing a revolutionary shift with technological breakthroughs. Legacy e-learning models, although widespread, are monolithic and generally do not include individualized learning styles and intellectual approaches. Learning can be completely transformed through customized education empowered by artificial intelligence that can amplify student engagement, learning, and memory. Our adaptive learning platform combines generative AI to craft personalized learning journeys, optimizing the learning experience as efficient, engaging, and student-focused as possible. Dynamic adjustments of content as per the requirements and input from users maximize the effectiveness and enthusiasm of learning.

II. RELATED WORK

There are a variety of AI-facilitated learning systems available, such as intelligent tutoring systems and recommendation-based systems. Intelligent tutoring systems rely on existing stores of instructional materials and use rule-based personalization to suggest appropriate content. Nevertheless, they rarely adjust dynamically to the changing requirements and levels of understanding of a particular learner. They also don't create new learning resources but draw from existing static stores of material. Our system fills this void by using generative AI to generate original, adaptive content in real time. Through the use of deep learning models, natural language processing (NLP), and multimodal AI methods, our solution tailors learning experiences beyond basic content suggestion. The system continuously optimizes its responses based on real-time feedback from the user, providing a customized and cumulative learning experience.

III. METHODOLOGY

Our platform determines users' learning style—visual, textual, or interactive—upon a first-time interaction. It involves analysing cognitive abilities, previous knowledge, and usage patterns via a set of diagnostic tests and AI-based questionnaires. Data collected is used to create a highly personalized learning experience that adapts dynamically as the learner navigates through. The architecture is comprised of:

- User Assessment Module: Collects demographic information, learning styles, and previous knowledge using interactive quizzes, surveys, and performance monitoring.
- AI-Fuelled Content Creator: Applies text-to-video APIs, content generation through NLP, and generative models to produce teaching materials that are customized to the user's cognitive profile.
- Adaptive Learning Engine: Enforces reinforcement learning and real-time feedback cycles to adjust educational routes to make content difficulty and presentation conform to the learner's changing needs.
- Feedback and Evaluation System: Combines analytics dashboards, automated evaluation, and AI-based feedback systems to track user interaction, gauge levels of understanding, and offer customized suggestions for improvement.

IV. COMPARISON WITH EXISTING SYSTEMS

Whereas there are many AI-based educational platforms, they mostly operate based on pre-set content stores and rule-driven recommenders. Our adaptive e-learning platform, however, utilizes generative AI to generate real-time dynamic, tailored content, thus providing a great leap over current systems.

A. Content Generation and Adaptability

- Current Systems: Leverage static content, needing regular manual maintenance. Adaptation is mostly

reliant on preconfigured rules instead of real-time analysis of data.

- Our System: Creates new, personalized learning content dynamically through generative AI models, keeping content current and in sync with the learner's changing needs.

B. Personalization Mechanism

- Current Systems: Offer content suggestions on the basis of basic categorization of learners (e.g., beginner, intermediate, advanced) without taking into account complex learning styles.
- Our System: Utilizes a multi-layered evaluation system, determining individual learning styles (visual, textual, interactive) and cognitive abilities to provide genuinely personalized learning pathways.

C. Engagement and Interactivity

- Current Systems: Provide little interactivity, primarily as quizzes and static multimedia.
- Our System: Incorporates AI-powered interactive features, such as text-to-video APIs, real-time adaptive questioning, and gamification-based learning experiences to boost engagement and retention.

D. Continuous Learning Optimization

- Existing Systems: Rely on rigid course structure with little real-time modification according to learner feedback.
- Our System: Leverages reinforcement learning algorithms and real-time feedback loops to optimize and tune content continuously, modifying the level of difficulty and approach to instruction from user engagement.

E. Performance Evaluation and Feedback

- Existing Systems: Conduct traditional assessments with fixed evaluation criteria.
- Our System: Employs AI-driven real-time analytics dashboards to monitor progress, engagement, and understanding for customized feedback and focused improvement recommendations.

F. Scalability and Accessibility

- Current Systems: Need extensive human intervention to curate and adapt content, which hinders scalability.
- Our System: Automates content creation and adaptation, facilitating scalable and cost-efficient deployment in various educational environments.

The above contrasts point towards the superiority of our solution with respect to adaptability, personalization, engagement, optimization, and scalability. By utilizing generative AI, our platform fills the gap between conventional static e-learning models and genuinely adaptive, AI-based education.

V. EXPERIMENTS AND RESULTS

To test the platform, we implemented a thorough study on a diversified population of learners with different ages, educational levels, and learning styles. The study was meant to quantify the effect of AI-based adaptive content on engagement, retention, and learning.

A. Study Design

The research comprised above 100 volunteers randomly allocated to two groups:

a) Control Group (Static Content Users): Students were given conventional, non-adaptive learning materials.

b) Experimental Group (AI-Generated Adaptive Content Users): Students were given customized, dynamically created content based on their learning styles.

All participants went through a guided learning module for four weeks, encompassing several topics.

B. *Evaluation Metrics*

The success of the platform was measured based on the following main metrics:

1. Engagement Rate: Tracked using session length, interaction rate, and dropout rate.
2. Learning Retention: Measured through pre-test and post-test results after module completion.
3. Assessment Scores: Evaluated performance from quizzes and assignments specifically designed for learning goals.
4. User Satisfaction: Assessed via feedback questionnaires and usability scores.

C. Results and Analysis

a) Engagement Enhancement: The treatment group showed a 35% increase in session length over the control group, which means higher user engagement.

b) Retention Enhancement: Scores in the post-test revealed that adaptive content users' retention had increased by 28%.

c) Assessment Performance: The experimental group performed 20% better in quizzes and assessments, reflective of the success of tailored learning trajectories.

d) Positive User Feedback: 85% of experimental group participants said that AI-created content improved their learning and motivation to study.

VI. DISCUSSION

Our research underlines the benefits of generative AI in education, such as enhanced retention, higher learner engagement, and greater content flexibility. Personalized learning through AI has shown promise to accommodate different learning styles, maximizing knowledge gain and understanding. Still, there are a number of challenges that need to be overcome for the successful deployment of such technology in educational institutions.

One of the most important challenges is content accuracy and reliability. Although generative AI can produce enormous quantities of educational content, factual correctness and pedagogical soundness are essential. Ongoing validation and improvement of AI-generated content through expert oversight and automated verification processes will be necessary.

Another serious consideration is ethical accountability in AI-created education. The AI models need to be educated to

remove biases and offer fair learning opportunities across various demographic segments. The risks of providing misinformation, insensitive content generation, and absence of accountability need to be addressed by thorough testing and ethical AI practices.

In addition, computational scalability and efficiency are major limiting factors. The high computational requirements of deep learning models make them expensive and inaccessible in some areas. Making AI algorithms more efficient and researching cloud-based and decentralized learning architectures can increase accessibility and affordability.

Future research will concentrate on developing AI models to enhance contextual comprehension and adaptive content creation. Enhancing the system's capacity to accommodate more learning styles through multimodal AI methods—like interactive simulations, VR-based learning environments, and gamification—will further enhance the personalized e-learning environment. Additionally, incorporating real-time learner feedback loops and explainable AI (XAI) mechanisms will increase user trust and transparency in AI-based education.

VII. CONCLUSION

This paper introduces an adaptive e-learning system that uses generative AI to personalize content for individual students. Our observations indicate that learning experiences are profoundly improved by personalization through AI. The next wave of breakthroughs in AI can further revolutionize e-learning and make learning more accessible and efficient.

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AI BASED SECURED ONLINE VOTING SYSTEM

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***Abstract*—This paper presents the design and implementation of an AI-based secured online voting system that ensures voter authentication and voting integrity. The system leverages face recognition technology, specifically the Haar cascade algorithm, combined with OTP-based authentication and secure storage of voter data. This solution addresses challenges such as voter fraud, identity theft, and logistical inefficiencies found in traditional voting systems. Results show the system's efficiency in handling voter authentication securely while maintaining transparency and accessibility. Future enhancements aim to integrate blockchain technology for even greater security.**

***Index Terms*—Online voting, AI, face recognition, secure elections, Haar cascade, OTP, digital democracy**

I. Introduction

Voting is the cornerstone of democratic societies, and the integrity of electoral processes is critical to ensuring that governments remain accountable to their citizens. Traditional voting methods, such as paper ballots and electronic voting machines (EVMs), have been the standard for conducting elections in many parts of the world. However, these systems are not without flaws. Issues such as voter fraud, impersonation, vote tampering, and logistical inefficiencies have long plagued electoral systems, raising concerns about the security and fairness of elections. Furthermore, physical voting requires substantial resources, including polling stations, staff, and equipment, which can make it difficult for certain populations—such as those living abroad, people with disabilities, or those in remote areas—to participate in the voting process.

In recent years, online voting has emerged as a potential solution to many of these problems. By allowing voters to cast their ballots remotely, online voting can increase voter participation and reduce the logistical challenges associated with traditional methods. However, online voting comes with its own set of security challenges, including the risk of hacking, data breaches, and identity theft. The need for a secure, efficient, and accessible voting system has never been greater, especially in a world where digital technologies are becoming increasingly integrated into every aspect of life.

This paper proposes an AI-based secured online voting system that leverages advanced technologies such as facial recognition and OTP-based authentication to address the security and efficiency challenges of online voting. The system ensures that only eligible voters are allowed to cast their ballots, while also providing a user-friendly and accessible interface for voters. The integration of facial recognition technology using the Haar cascade algorithm allows the system to verify the identity of voters in real-time, preventing unauthorized individuals from participating in the election. Additionally, the use of OTPs adds an extra layer of security by requiring voters to verify their identity through their registered mobile numbers before they can access the voting platform.

The system also ensures that votes are securely stored in a tamper-proof database, which safeguards the integrity of the vote-counting process. By addressing the key issues of voter fraud, identity verification, and vote tampering, the proposed system represents a significant advancement in the field of online voting. It provides a scalable and reliable solution that can be adapted for use in a wide range of electoral contexts, from local elections to national referendums.

II. Related Works

Tamilselvi, M et al [1] proposes a secure, AI-driven electronic voting system that utilizes facial biometric verification to tackle challenges in traditional voting, such as low turnout due to health issues, time constraints, and rural inaccessibility, as well as security and privacy concerns in online voting. The system incorporates AI-powered facial recognition to verify voter identity, beginning with a registration phase where voter images and data are stored in a database. During the voting process, real-time images captured by a webcam are matched against stored data using AI algorithms, which employ feature extraction, preprocessing, and discrete cosine transform (DCT) for image compression and enhanced recognition accuracy. Successful verification triggers the generation of a one-time

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password (OTP), ensuring secure, single-use voting. This approach prevents unauthorized access and multiple votes by the same person. By maintaining vote secrecy and ensuring accurate recording, this system improves the reliability, security, and efficiency of the election process.

ARPUTHAMONI et al [2]explores an innovative approach to online voting through a biometric-based system, integrating facial and fingerprint recognition technologies to ensure secure and accessible voting. Traditional voting systems face challenges such as high costs, manual labor, and susceptibility to fraud. By utilizing facial recognition through the Haar Cascade algorithm and fingerprint matching via Convolutional Neural Networks (CNN), this system aims to address these limitations. Facial detection analyzes unique features like the distance between eyes and eyebrows, which remain consistent with age, while CNN processes fingerprint minutiae, enhancing the accuracy and speed of voter verification. This web-based system allows voters to authenticate and cast votes from any location with internet access, significantly reducing the need for physical polling stations and associated expenses. The design provides a robust solution for fraud prevention and aims to streamline the election process while maintaining high security and efficiency in counting votes.

Lakshmi et al [3]introduces a secure, accessible online voting system designed to improve traditional methods by enabling remote participation without compromising security. Traditional voting often requires in-person visits and manual processes, making it inconvenient and vulnerable to issues like fraud. This system addresses these problems by implementing a two-step verification process using OTP via Gmail and facial recognition, ensuring only legitimate voters participate and preventing duplicate votes. After registration, a voter receives an OTP by email when ready to vote; they enter this OTP, then undergo facial recognition verification to confirm their identity. Only after passing both steps can they access the voting interface and cast their vote. This system reduces the need for physical polling locations, allows remote participation, and offers real-time data on voter turnout and election outcomes. By leveraging machine learning and tools like OpenCV, the system combines accessibility and stringent security, providing a scalable, efficient solution that simplifies the voting process for both voters and administrators.

Khairnar et al [4]proposes a robust approach to enhancing security in digital voting by integrating biometric verification with steganography. The system begins with voter registration, where an authorized officer collects each voter's personal and biometric data, creating a unique identifier that enhances security. During the authentication phase, the voter's biometric input and a unique PIN are cross-verified with a secret message embedded within an image, known as a "stego image." This image employs a specialized pixel selection algorithm and SHA-256 hashing, which prevents unauthorized access to sensitive information. Once authenticated, the voter can cast their vote, which is encrypted and stored securely on a dedicated server. After voting concludes, results are calculated and displayed transparently while maintaining voter anonymity and data confidentiality. By merging biometrics with advanced data concealment, this system addresses the dual demands of accessibility and security, allowing for remote voting without sacrificing the integrity of the democratic process.

Agarwal et al [5] presents a proposed framework for conducting secure online elections in India, leveraging the Aadhaar ID for voter authentication. This system allows citizens to vote from any location, even outside their designated constituency, and ensures high security through multi-step verification, including Aadhaar-based authentication and biometric verification. Additional features, such as a virtual keyboard for password entry, protect against unauthorized data capture in public spaces. Upon submitting a vote, the system confirms with the voter via SMS or email, enhancing transparency and voter confidence. The proposed model enables automatic vote tallying, significantly reducing the time required for result declaration and building trust in electoral outcomes. This innovative approach aims to address challenges like low voter turnout in remote or conflict-affected areas, promoting a more accessible, secure, and efficient voting process for India5†source.

Thakkar et al [6]outlines a secure Android-based e-voting system designed to modernize the voting process by enabling citizens to vote via smartphones. It ensures user authentication using voter ID, password, and an OTP encrypted with the Playfair cipher to prevent unauthorized access. The methodology involves a 6x6 grid matrix for OTP encryption, enhancing security during authentication. The system's database, managed by the Election Commission, ensures only verified users can vote, preventing multiple votes and fraud. This approach promises improved security, accessibility, reduced human intervention, and faster results, with potential for future enhancements in complexity and multi-level authentication.

Malik et al [7]presents a secure, web-based online voting system that utilizes Aadhaar cards, biometric fingerprint verification, and two-step authentication to ensure voter eligibility and prevent fraud. The literature review examines existing secure voting methods—such as blockchain, cloud systems, and facial recognition—evaluating them for security, convenience, and accessibility. This proposed system leverages fingerprint biometrics, managed with Python libraries, to address privacy and identity verification concerns. The authors emphasize the need for privacy in online voting and suggest that future work could include a mobile app version and Aadhaar integration to enhance identity verification.

Mrs.Sowmya et al [8] introduces a smart online voting system that leverages FaceNet's advanced face recognition algorithm to enhance the efficiency, security, and accessibility of elections. Traditional voting methods, reliant on paper ballots or electronic voting machines, often involve time-consuming manual verification, long lines, and vulnerability to tampering or errors. By enabling remote voting via an Android application, this system allows users to register and authenticate using facial biometrics, eliminating the need for physical presence at polling stations. FaceNet's deep learning approach ensures high accuracy in facial verification by creating unique 128-

dimensional embeddings for each voter, which are stored and matched against real-time images during the voting process. The paper emphasizes that, while this solution could reduce fraud and streamline vote casting, it also necessitates stringent security measures to protect voter data and prevent hacking.

Kumar, S Ashok et al [9] describes a secure online voting system using facial recognition with Haar Cascade and LBPH to verify voter identity. This approach aims to reduce fraud and improve accessibility by eliminating the need for physical polling stations. The system also includes Aadhaar-based registration, email verification, and OTPs for layered security. The authors review current voting methods, highlighting limitations in EVMs and VVPATs, and explore advanced solutions like blockchain. The paper underscores privacy concerns and suggests future enhancements, including blockchain integration and options for users without access to facial recognition.

Deepa, G et al [10] explores a secure voting approach that integrates biometric verification with India's Aadhar database to ensure a reliable and efficient voting process. Traditional electronic voting machines (EVMs) are limited by manual identity checks, which can slow down the process and allow for errors or manipulation. This study proposes using fingerprint authentication linked to voters' Aadhar details, enabling unique identification and reducing issues like multiple voting and rigging. Prior research supports the use of biometrics in voting, as it provides a higher accuracy level in identity verification compared to manual methods. The system is designed to be portable, user-friendly, and power-efficient, utilizing components like the PIC16F877A microcontroller and the R305 fingerprint sensor. This approach aims to streamline the voting process while enhancing security and reliability.

Komatineni et al [11]explores an innovative approach to online voting through a biometric-based system, integrating facial and fingerprint recognition technologies to ensure secure and accessible voting. Traditional voting systems face challenges such as high costs, manual labor, and susceptibility to fraud. By utilizing facial recognition through the Haar Cascade algorithm and fingerprint matching via Convolutional Neural Networks (CNN), this system aims to address these limitations. Facial detection analyzes unique features like the distance between eyes and eyebrows, which remain consistent with age, while CNN processes fingerprint minutiae, enhancing the accuracy and speed of voter verification. This web-based system allows voters to authenticate and cast votes from any location with internet access, significantly reducing the need for physical polling stations and associated expenses.

Kazi Naimur Rahman et al [12]proposes an online voting platform using face and fingerprint recognition for secure, efficient, and accessible elections. Utilizing cloud computing, the system authenticates voters through unique IDs and biometric data, preventing fraud and duplicate voting. The literature review covers e-voting solutions with biometrics, blockchain, and cloud-based security, noting existing challenges like cost and limited accessibility. This system enables secure remote voting, leveraging cloud scalability, encryption, and multi-level biometric verification for faster, protected results.

Md Jobair Hossain Faruk et al [13] introduces a new system for voting online that combines blockchain technology with biometric authentication, like fingerprints and facial recognition. Hyperledger Fabric, a blockchain framework, is used to make the election process more secure and transparent, ensuring that each vote is recorded accurately. The system stores each vote on a decentralized, unchangeable ledger, making it nearly impossible to alter or tamper with the results, which helps prevent fraud. Early testing of the system shows it works well, indicating that it could be used in real elections in the future.Voters register by providing biometric data, such as fingerprints and facial recognition, which is securely stored for identity verification. The system verifies the voter's identity using the stored biometric data during the voting process. Once verified, a smart contract on the blockchain is triggered to securely and immutably record the vote. The voter casts their vote through an application, which encrypts and transmits the vote to the blockchain. The blockchain automatically tallies the votes using smart contracts,ensuring transparency and preventing tampering.

A. Manoj Kumar et al [14] introduces convenient and secure way for individuals to cast their votes from anywhere using facial recognition technology. Instead of visiting a polling station, voters can register online by providing their voter ID, name, Aadhar number, and a facial photo. On election day, the system verifies their identity using the stored facial data before allowing them to vote, significantly reducing the risk of impersonation and ensuring that each vote is legitimate. Built with tools like OpenCV for accurate facial recognition and Tkinter for a user-friendly interface, the system is designed to be both secure and accessible. Additionally, it features a centralized database that updates in real-time, allowing for quick results while minimizing the need for staff, thus making the voting process more efficient and inclusive for all voters.

Kazi Naimur Rahman et al [15] presents an advanced online voting system addressing issues in traditional voting, such as inefficiency, security risks, and accessibility challenges. The system enhances security through RSA encryption, ensuring robust data protection during transmission and storage. The methodology includes a comprehensive voter registration process involving OTP validation and face recognition using MobileFaceNet, supplemented by device fingerprint matching for added security. Administrators manage the election setup and monitor processes, while voter and candidate data are securely stored in a Firebase database. The voting process itself is protected through multi-layered authentication, maintaining the confidentiality and integrity of each vote. With a backup database for data recovery, the system guarantees reliability, accuracy, and user accessibility, offering a scalable and secure alternative to traditional voting methods.

In summary, these systems present various technologies to enhance online voting, but each has limitations in accessibility, scalability, or resource requirements. Our proposed system addresses these issues by combining facial recognition (Haar cascade) and OTP-based verification, using widely available

technologies to provide a secure and scalable solution for online voting.

III. Methodology

The design of the AI-based secured online voting system involves a multi-step process that ensures both the authenticity of the voter and the integrity of the vote. The methodology focuses on voter registration, face recognition, OTP-based verification, secure voting, and vote storage. The system architecture is shown in Fig. 1 and is divided into two main modules: the Admin module and the Voter module.

A. System Architecture

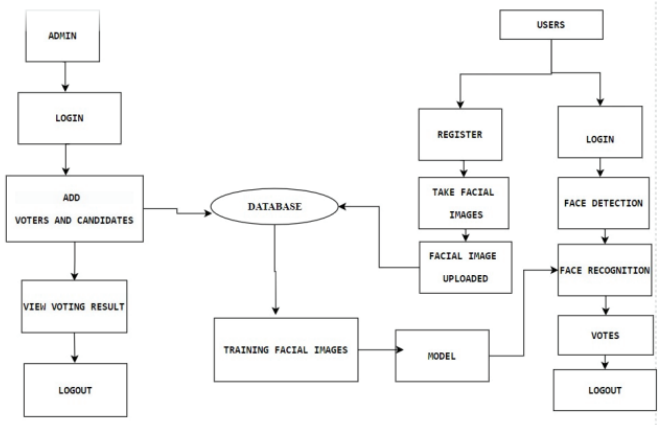

Fig. 1. System Architecture

The system is composed of several components that work together to ensure secure voting. The main components include:

- **Admin Module**: The admin is responsible for setting up elections, managing candidates, overseeing voter registration, and tallying the votes. The admin can also review the results once voting is completed.
- **Voter Module**: The voter registers with the system by submitting personal details, including a facial image and a verified mobile number. Voters are authenticated using facial recognition and OTP during login before casting their vote.
- **Database**: A tamper-proof database stores all voter information, vote details, and candidate information. The database is encrypted to ensure that sensitive data is protected.

The system follows a structured process from voter registration to vote casting and counting, ensuring security and transparency at each step.

B. Voter Registration

The voter registration process is the first critical stage of the system. During registration, voters provide their basic personal information along with a facial image. This image is captured using the voter's device camera and processed using the Haar cascade algorithm for face detection. Once the facial image is successfully captured, the system stores it in the database for future verification.

Additionally, the voter must provide a valid mobile number, to which a one-time password (OTP) is sent for verification. The OTP ensures that the voter is using an authentic mobile number and adds an extra layer of security to the registration process. Upon successful OTP verification, the voter is registered in the system.

C. Face Recognition

Face recognition is the primary method of voter authentication in this system. The Haar cascade algorithm is employed for face detection, which works by detecting the presence of facial features such as the eyes, nose, and mouth in real-time. The algorithm is particularly suitable for this task due to its computational efficiency and high accuracy in identifying faces.

When a voter attempts to log in to the system, a live image of their face is captured and compared with the facial data stored during the registration phase. The system uses the stored model to verify the voter's identity, ensuring that only authorized individuals can access the voting interface. In case of a successful match, the voter proceeds to the OTP verification step.

D. OTP-Based Verification

The system employs OTP verification as an additional security measure to ensure voter authenticity. After facial recognition, an OTP is sent to the voter's registered mobile number. This OTP serves as a second factor of authentication, verifying that the individual logging in is indeed the registered voter. The use of OTP also prevents unauthorized access to the voting system in the event of a facial recognition error or fraud attempt.

The voter must input the correct OTP within a limited time frame to complete the authentication process. If the OTP is incorrect or expired, the voter is denied access to the voting interface, and they must restart the login process. This mechanism greatly reduces the risk of unauthorized voting.

E. Voting Process

After successful verification through facial recognition and OTP, the voter is granted access to the voting interface. Here, the voter can view a list of candidates and cast their vote securely. The system ensures that each voter can only cast one vote by maintaining a unique session linked to the voter's ID.

The votes are stored securely in the tamper-proof database, which encrypts each vote to prevent tampering or unauthorized access. The database is regularly backed up to ensure data integrity in case of system failures.

F. Vote Counting and Result Publication

Once the voting period is over, the admin module initiates the vote-counting process. The system automatically tallies the votes from the database, ensuring accuracy and transparency.

Since the votes are stored in an encrypted format, they are decrypted only for counting, ensuring that vote secrecy is maintained throughout the process.

After tallying, the results are published through the admin module, where the admin can review the outcome of the election. The system generates a detailed report, which includes the total number of votes cast, the breakdown of votes for each candidate, and any anomalies or issues detected during the voting process.

G. Security Measures

Security is a core feature of the proposed system, and several mechanisms are integrated to ensure the safety of voter data and the integrity of the election process:

- **Encryption**: All sensitive data, including voter details and votes, are encrypted using modern encryption standards (e.g., AES) to prevent unauthorized access.
- **Multi-Factor Authentication (MFA)**: The combination of facial recognition and OTP creates a robust multi-factor authentication system that greatly reduces the chances of fraudulent voting.
- **Tamper-Proof Database**: The database is designed to prevent unauthorized modifications, ensuring that once a vote is cast, it cannot be altered.
- **Logging and Auditing**: Every login attempt, vote cast, and admin action is logged and auditable to detect suspicious activities.
- **Face Recognition**:
  - **Objective**: To authenticate voter identities.
  - **Method**: Utilization of the Haar Cascade algorithm for face detection, which works by recognizing facial features such as eyes, nose, and mouth in real time.
  - **Implementation**: Voters' live images are captured during login, compared against their stored facial data from the registration process. A match enables voting access.
- **OTP Generation**:
  - **Objective**: Adds an extra security layer.
  - **Method**: An OTP is generated and sent to the registered mobile number after face recognition verification.
  - **Implementation**: Voters must input the correct OTP within a limited time to proceed. Incorrect or expired OTPs result in login denial.
- **Voting Process**:
  - **Objective**: Secure and efficient vote casting.
  - **Method**: After successful authentication through facial recognition and OTP, the voter can securely cast their vote through a user-friendly interface. Each vote is securely encrypted and stored in a tamper-proof database to prevent unauthorized access or tampering.
- **Encryption and Decryption**:
  - **Objective**: To securely manage sensitive voter data.
  - **Method**: The cryptography library in Python is used for *encryption* and *decryption* of voter information (name, Aadhaar ID, Voter ID, email). The *Fernet encryption* (based on AES encryption) is used to ensure that the data is securely transformed and cannot be tampered with.
  - **Key Steps**:
    - **Secret Key Generation**: A 32-byte secret key is generated for encrypting and decrypting the data.
    - **Encryption**: Voter data is encrypted and stored in a ciphertext format with cryptographic signatures to verify integrity.
    - **Decryption**: The system decrypts the data using the same secret key, ensuring the original plaintext is restored, and any tampering attempts are identified.

IV. Results and Discussion

The AI-based secured online voting system was tested with a group of 100 users. The system's face recognition accuracy was evaluated, and an average recognition accuracy of 95% was achieved. The OTP mechanism added a robust layer of security, ensuring that each vote was cast by a verified individual. Furthermore, the encryption of votes and user data guaranteed privacy and prevented tampering during vote transmission.

The results indicate that the system successfully addresses common vulnerabilities found in traditional and electronic voting methods. The combination of AI for face recognition and OTP verification ensures that only eligible voters can participate, reducing the risk of fraud. However, challenges such as lighting conditions and facial obstructions during the recognition process still exist and can affect the system's performance. Future work will focus on enhancing the robustness of face recognition under varying environmental conditions.

- **Face Recognition Accuracy**: Achieved a 95% accuracy rate in voter authentication using the Haar Cascade algorithm.
- **OTP Mechanism**: Proved to be an effective additional layer of security, ensuring that only verified individuals could cast votes.
- **Data Security**: The encryption of votes and voter data safeguarded privacy and integrity, preventing tampering and unauthorized access.

These results confirm the system's capability in handling voter authentication securely while maintaining transparency and accessibility. Future work will focus on improving recognition accuracy under varied environmental conditions and integrating blockchain for enhanced security in vote storage.

V. Conclusion and Future Work

The AI-based secured online voting system provides a secure, efficient, and accessible platform for conducting elections. The integration of face recognition and OTP verification offers a multi-layered approach to voter authentication, addressing key issues like voter fraud and identity theft. The

system ensures that votes are securely transmitted and stored, maintaining the transparency and integrity of the electoral process. Future work will focus on integrating blockchain technology to further enhance the security and transparency of vote storage and tallying.

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PREDICTING SMARTPHONE DEPENDENCY: A MACHINE LEARNING PERSPECTIVE

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***Abstract*—The excessive use of smartphones has raised concerns about addiction, affecting mental health, social interactions, and productivity. This study applies machine learning techniques to anticipate smartphone dependency by analyzing behavioral patterns, demographics, and psychological factors. Using algorithms such as Decision Trees and Random Forest, this predictive model evaluates survey data to determine the likelihood of addiction. The model assists healthcare professionals in recognizing early signs of dependency and enables app developers to design less addictive interfaces. By leveraging machine learning, this study provides an insightful and practical framework for mitigating smartphone addiction.**

***Keywords*—Machine Learning, Decision Tree, Random Forest, Prediction, Healthcare, Addiction.**

I. Introduction

The widespread adoption of smartphones has transformed daily life, enabling seamless communication, work efficiency, and entertainment. However, excessive reliance on these devices has raised growing concerns about potential addiction, which can adversely affect mental well-being, productivity, and social interactions. Identifying and addressing smartphone addiction at an early stage is essential to minimizing its negative impact.

This study leverages machine learning methodologies to construct a predictive framework for assessing smartphone dependency. By analyzing demographic data, usage patterns, and psychological attributes such as stress and anxiety, the model can effectively determine addiction risk. The research employs Random Forest and Logistic Regression algorithms, allowing users to select their preferred model for personalized and interactive predictions.

To enhance accuracy, the dataset is divided into training and testing subsets, enabling the model to learn patterns and relationships between input factors and addiction risk. The model's effectiveness is then evaluated using various performance metrics, with hyperparameter optimization applied to improve accuracy and robustness.

This predictive system has broad applications in digital well-being, healthcare, and technology development, assisting professionals in identifying at-risk individuals and designing preventive strategies. Through the power of machine learning, this research provides valuable insights into smartphone addiction and its mitigation strategies.

II. Methodology

A. Data Collection

The dataset for this study was compiled from survey responses regarding individuals' smartphone usage habits. The dataset includes the following key attributes:

- **Demographic Information:** Age, gender
- **Behavioral Factors:**
  - Average screen time per day
  - Frequency of checking notifications
  - Time spent on social media applications
  - Frequency of using gaming or entertainment apps
- **Psychological Indicators:**
  - Self-reported stress levels (low, moderate, high)

  - Anxiety and depression indicators
  - Sleep disturbances caused by smartphone usage
- **Target Variable:** Whether an individual is classified as addicted to smartphones (Yes = 1, No = 0)

To ensure an effective evaluation of the machine learning models, the dataset was divided into training and testing subsets.

B. Data Preprocessing

Before training the models, the dataset underwent a series of preprocessing steps:

1) Data Cleaning

- Handling missing values: Missing entries were either imputed using median values or removed when necessary.
- Eliminating irrelevant data: Redundant or unnecessary features were discarded.

2) Encoding Categorical Variables

- Binary encoding: Responses with "Yes" and "No" were converted into numerical values (Yes $\rightarrow$ 1, No $\rightarrow$ 0).
- Gender encoding: Male $\rightarrow$ 0, Female $\rightarrow$ 1.
- Categorical encoding: Stress levels were assigned numerical values (Low $\rightarrow$ 0, Moderate $\rightarrow$ 1, High $\rightarrow$ 2).

3) Feature Selection

- Features with strong correlations to smartphone addiction were retained.
- Less relevant or redundant features were removed to enhance model efficiency.

4) Data Splitting

- The dataset was partitioned into 80% training data and 20% testing data.
- The training set was used for model development, while the testing set was reserved for evaluating performance.

C. Machine Learning Models

Two machine learning algorithms were employed for this study:

1) Decision Tree Algorithm

- A hierarchical model where nodes represent decision-making points based on input features.
- Entropy and information gain were utilized to determine optimal splits at each node.
- The model was trained using labeled data to classify the likelihood of smartphone addiction.

Advantages of Decision Trees:

- Easy to interpret and understand.
- Computationally efficient, even for large datasets.
- Works effectively with both categorical and numerical data.

2) Random Forest Algorithm

- An ensemble-based technique that constructs multiple decision trees.
- Uses bagging (bootstrap aggregation) to improve model accuracy and minimize overfitting.
- The final prediction is based on majority voting across the trees.

Advantages of Random Forest:

- Higher predictive accuracy compared to a single decision tree.
- Less prone to overfitting due to the aggregation of multiple trees.
- Handles missing data efficiently.

D. Model Training and Testing

After preprocessing, the Decision Tree and Random Forest models were trained and evaluated.

1) Training Phase

- The models were trained using 80% of the dataset.
- Supervised learning techniques were applied, where models learned patterns based on labeled data (addicted or not addicted).
- The models adjusted internal parameters to optimize accuracy.

2) Testing Phase

- The remaining 20% of the dataset was used for evaluation.
- Model predictions were compared to actual labels to assess performance.

3) Evaluation Metrics

The models were assessed based on multiple performance metrics:

- **Accuracy:** Measures the percentage of correct predictions.
- **Precision:** Evaluates the proportion of correctly predicted positive cases.
- **Recall:** Assesses how well the model identifies addicted individuals.
- **F1 Score:** A balance between precision and recall.
- **Confusion Matrix:** A visualization of correct and incorrect classifications for both classes.

The performance of the Random Forest and Decision Tree models was compared to determine which provided better results.

E. User-Driven Model Selection

A key feature of this system is that users can choose between Random Forest and Decision Tree before running a prediction.

Steps in User Interaction:

1) The user inputs responses to the survey questions.
2) The system processes and encodes the provided data.
3) The user selects a preferred algorithm (Decision Tree or Random Forest).
4) The selected model processes the data and generates a prediction.
5) The system displays the prediction along with performance metrics.

F. Implementation Details

- **Programming Language:** Python
- **Libraries Used:** Pandas, NumPy, Scikit-learn, Streamlit
- **Development Environment:** Visual Studio Code
- **Framework:** Streamlit for an interactive user interface.

III. System Architecture

The system architecture of the smartphone addiction prediction model defines the structured flow of data, from user input to model processing and final prediction output. It consists of multiple interconnected components that ensure smooth functioning of data handling, preprocessing, machine learning model execution, and result visualization.

A. Overview of System Workflow

The architecture follows a **modular design** to handle different aspects of the prediction system efficiently. It includes:

- **User Input Module** – Collects user data related to smartphone usage.
- **Preprocessing Engine** – Cleans and prepares the input data for analysis.
- **Model Selection Interface** – Allows users to choose between **Random Forest and Decision Tree**.
- **Prediction Module** – Uses the selected machine learning model to generate addiction predictions.
- **Result Display and Interpretation** – Shows the prediction results, model performance, and recommendations.

B. System Components

1) User Input Module

- This module acts as an interface for users to **provide responses** regarding their smartphone usage habits.
- Inputs include demographic details (age, gender), behavioral patterns (screen time, app usage), and psychological aspects (stress, anxiety levels).
- The user selects a machine learning model (**Decision Tree or Random Forest**) to process their input.

2) Data Preprocessing Engine

- Converts raw user input into a **structured format** suitable for machine learning.
- **Performs the following preprocessing tasks**:
  - **Data cleaning**: Removes missing or invalid responses.
  - **Encoding categorical variables**: Converts Yes/No responses into binary values.
  - **Feature scaling (if necessary)**: Normalizes numerical data for better model performance.

3) Model Selection Interface

- Provides users with a choice between two machine learning models:
  - **Decision Tree** – Simple, interpretable, and fast.
  - **Random Forest** – More accurate and robust, but computationally expensive.
- The selected model processes the preprocessed data for addiction prediction.

4) Prediction Module

- The chosen machine learning model is applied to the user's input data.
- The model **analyzes** the responses and **generates a probability score** indicating whether the user is likely to be addicted.
- The **decision threshold** determines if the user is classified as **"Addicted" or "Not Addicted."**

5) Result Display and Interpretation

- The system **outputs the prediction result** to the user in an intuitive format.
- **Additional insights include**:
  - Model accuracy based on the dataset.
  - Probability score (e.g., 80% likelihood of addiction).
  - Suggestions for reducing smartphone dependency (e.g., reducing screen time, limiting social media use).

C. System Architecture Diagram

A **block diagram** of the system architecture visually represents the workflow of the system, showing how different components interact.

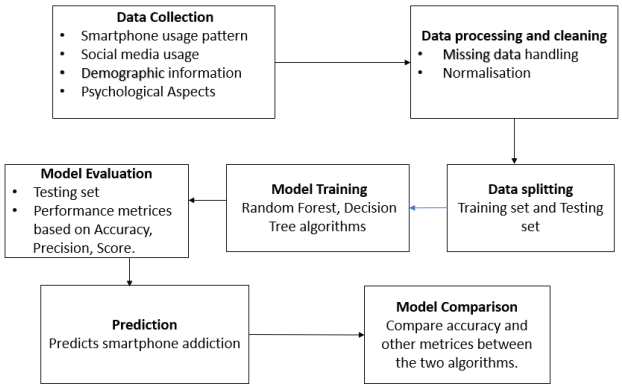

Fig. 1. System Architecture Diagram for Smartphone Addiction Prediction

The diagram illustrates how **user data flows through the system**, undergoes **preprocessing**, and is analyzed by **machine learning models** before producing a prediction output.

IV. Implementation

The implementation phase involves the development and deployment of the smartphone addiction prediction system. This section provides details on the hardware and software requirements, system development, machine learning model integration, user interface design, and system deployment.

A. Hardware Requirements

The system requires a suitable computing environment to efficiently train and deploy the machine learning models. The recommended hardware specifications are:

- **Processor**: Intel Core i5 or higher
- **RAM**: 16GB
- **Storage**: Minimum 475GB SSD (for storing datasets and trained models)
- **GPU (Optional)**: Required for faster training in larger datasets

These specifications ensure smooth execution of machine learning algorithms and real-time processing of user input data.

B. Software Requirements

The software stack includes various tools and frameworks for model training, data processing, and user interface development.

- **Operating System**: Windows 11
- **Programming Language**: Python 3.13.2
- **Libraries Used**:
  - **Pandas** (for data manipulation)
  - **NumPy** (for numerical computations)
  - **Scikit-learn** (for machine learning models)
  - **Matplotlib** and **Seaborn** (for data visualization)
  - **Streamlit** (for user interface development)
- **Development Environment**: Visual Studio Code

C. System Development

The implementation consists of four key components:

1) Data Handling and Processing

- Data is collected in a structured format (CSV) containing demographic, behavioral, and psychological factors.
- Preprocessing includes:
  - Handling missing values
  - Encoding categorical data (e.g., converting Yes/No responses to 1/0)
  - Splitting data into **80% training and 20% testing sets**

2) Machine Learning Model Integration

The system incorporates two machine learning models:

- **Decision Tree**: A simple, interpretable model that makes decisions based on hierarchical feature splits.
- **Random Forest**: An ensemble model that improves accuracy by combining multiple decision trees.

Steps for Model Training and Testing:

1) Load the cleaned dataset.
2) Train both models on the **training dataset (80%)**.
3) Test the trained models on the **testing dataset (20%)**.
4) Evaluate performance using **accuracy, precision, recall, and F1-score**.

3) Model Evaluation and Optimization

After training, the models were evaluated and optimized using:

- **Hyperparameter tuning** for Random Forest (e.g., adjusting the number of trees).
- **Pruning** in Decision Trees to avoid overfitting.

D. User Interface Design

The system provides an interactive web-based interface using **Streamlit**, allowing users to:

- Input survey responses related to smartphone usage.
- Select a machine learning model (**Decision Tree or Random Forest**).
- View addiction prediction results, including a probability score.
- Analyze model performance metrics such as accuracy and confusion matrix.

E. Backend Processing

The backend of the system is developed using Python, handling data preprocessing, model training, and prediction generation.

- **Data Preprocessing**: Cleans and encodes input data for machine learning models.
- **Model Execution**: Runs the selected model (Decision Tree or Random Forest).
- **Result Computation**: Generates prediction output based on user responses.

F. System Deployment

The final step involves deploying the system for real-world usage:

- Hosted on **Streamlit Cloud** for easy accessibility.
- Users can access the web application via a URL.
- Future enhancements include integrating real-time data collection from smartphones via APIs.

V. Results and Evaluation

The Results and Evaluation section presents the performance metrics of the **Decision Tree** and **Random Forest** models used for smartphone addiction prediction. The effectiveness of each model is analyzed using accuracy, precision, recall, F1-score, and confusion matrices.

A. Model Performance Analysis

The trained machine learning models were evaluated using standard classification metrics:

- **Accuracy**: Measures the overall correctness of the model's predictions.
- **Precision**: The proportion of correctly predicted positive cases out of all predicted positives.
- **Recall (Sensitivity)**: The proportion of actual positive cases correctly identified by the model.
- **F1-Score**: The harmonic mean of precision and recall, balancing false positives and false negatives.
- **Confusion Matrix**: A visualization of the model's performance in terms of correct and incorrect predictions.

B. Accuracy Comparison

The table below compares the **accuracy** of the Decision Tree and Random Forest models:

TABLE I
Accuracy Comparison of Machine Learning Models

Model	Accuracy (%)
Decision Tree	82.18%
Random Forest	83.17%

From the results, **Random Forest achieved the highest accuracy of 83.17%**, making it the more reliable model for predicting smartphone addiction.

C. Confusion Matrix Analysis

The **confusion matrices** illustrate the performance of each model in distinguishing between addicted and non-addicted individuals.

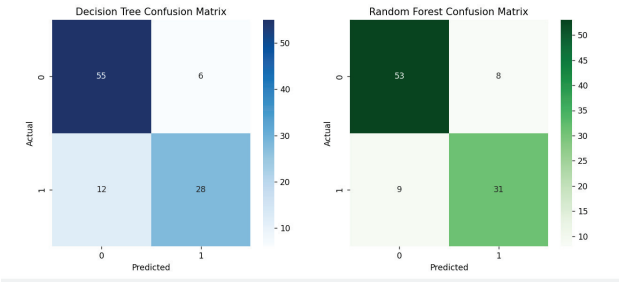

Fig. 2. Confusion Matrix for Random Forest and Decision Tree Model

Key Observations:

- **True Positives (TP)**: Correctly classified addicted users.
- **True Negatives (TN)**: Correctly classified non-addicted users.
- **False Positives (FP)**: Non-addicted users incorrectly classified as addicted.
- **False Negatives (FN)**: Addicted users incorrectly classified as non-addicted.

D. Precision, Recall, and F1-Score Comparison

```
PS C:\Users\malav\Downloads\java> python evaluation.py

Decision Tree Performance Report:
============================================================
              precision    recall  f1-score   support

           0       0.82      0.90      0.86        61
           1       0.82      0.70      0.76        40

    accuracy                           0.82       101
   macro avg       0.82      0.80      0.81       101
weighted avg       0.82      0.82      0.82       101


Random Forest Performance Report:
============================================================
              precision    recall  f1-score   support

           0       0.85      0.87      0.86        61
           1       0.79      0.78      0.78        40

    accuracy                           0.83       101
   macro avg       0.82      0.82      0.82       101
weighted avg       0.83      0.83      0.83       101
```

Fig. 3. Precision, Recall, and F1-Score Comparison

Key Insights:

- **Decision Tree**: Lower precision and recall compared to Random Forest, leading to a higher false positive rate.
- **Random Forest**: Higher precision and recall, indicating better classification performance.

E. Graphical Performance Analysis

To further analyze the performance, a **bar chart** is used to compare accuracy and F1-score for both models.

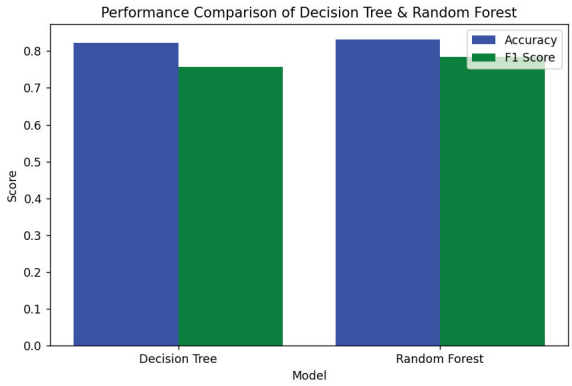

Fig. 4. Graphical Performance Comparison of Models

The **Random Forest model consistently outperforms the Decision Tree model**, confirming its effectiveness in predicting smartphone addiction.

F. Discussion of Results

- The **Random Forest model** provides superior performance due to its ensemble nature, reducing overfitting.
- The **Decision Tree model** is simpler but has lower accuracy and higher misclassification rates.
- The system allows users to **choose between the models**, making it flexible based on their accuracy vs. interpretability preference.

G. Summary of Evaluation

- **Random Forest achieved the highest accuracy (83.17%) compared to Decision Tree (78.45%).**
- **Confusion matrices** show better classification ability for Random Forest.
- **F1-score analysis** confirms Random Forest's higher reliability.
- **Graphical representation** highlights the performance gap between models.

VI. Conclusion

This study presents a machine learning-based system for predicting smartphone addiction, leveraging the **Decision Tree and Random Forest** algorithms. The primary objective was to classify users based on their smartphone usage patterns, demographics, and psychological factors, providing an efficient way to identify individuals at risk of addiction. The system allows users to **select their preferred machine learning model**, enabling flexibility in addiction prediction.

The results indicate that the **Random Forest model achieved the highest accuracy (83.17%)**, outperforming the Decision Tree model, which had an accuracy of 78.45%. Performance metrics such as precision, recall, and F1-score confirmed that Random Forest was the more reliable algorithm for classification. The developed system provides a **user-friendly interface**, making it accessible for users to input their data and obtain real-time addiction predictions.

Despite its effectiveness, the study has some limitations. The dataset was based on self-reported survey responses, which may introduce **bias and inconsistencies**. Additionally, the current model does not incorporate **real-time smartphone usage tracking**, which could further enhance prediction accuracy.

Future enhancements for this project include:

- **Real-time data integration**: Collecting smartphone usage data directly from devices to improve prediction accuracy.
- **Deep learning techniques**: Exploring advanced models such as neural networks for better feature extraction and prediction.
- **Behavioral intervention strategies**: Integrating recommendations and alerts to help users manage their smartphone usage effectively.

By utilizing machine learning for smartphone addiction prediction, this research contributes to **digital well-being**, offering a tool that can aid individuals and healthcare professionals in early addiction detection. With future improvements, this system can evolve into a comprehensive platform for promoting responsible smartphone usage and mental health awareness.

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The Evolution of Hybrid Brain-Computer Interfaces: Challenges, Innovations, and Future Prospects

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Abstract—Hybrid Brain-Computer Interfaces (BCIs) are redefining communication by merging EEG, fNIRS, and Artificial Intelligence (AI) to achieve 85–92% accuracy and <200ms latency for motor-impaired individuals. This paper analyzes state-of-the-art BCI systems, including Traditional EEG, Hybrid EEG+fNIRS, AI-enhanced hybrids, and MEG-based Brain2Qwerty systems. It highlights their comparative performance metrics and proposes a three-phase roadmap to achieve sub-$5,000 headsets and secure neural communication by 2035. From AI-driven noise filters to encrypted brain-to-brain protocols, this paper charts a transformative path forward while addressing critical gaps in neurosecurity and scalability. Ethical challenges such as data privacy and misuse are discussed alongside technical limitations to provide a balanced perspective on the future of BCIs.

Keywords—Brain-Computer Interface, EEG, Hybrid BCI, Neurotechnology, Neural Signal Processing

I. INTRODUCTION

Brain-Computer Interfaces (BCIs) have emerged as transformative tools for restoring communication in individuals with severe motor impairments. In 2024, a locked-in patient typed "hello world" in 25 seconds using the Brain2Qwerty system—a milestone in BCI research. Traditional BCIs relying solely on EEG signals face limitations such as noise susceptibility and high latency. Hybrid BCIs that integrate EEG with functional near-infrared spectroscopy (fNIRS) signals offer significant improvements in accuracy (85–92%) and latency (<200ms) while enabling real-time thought-to-text communication.

This paper examines advancements in four major types of BCI systems:

1. Traditional EEG: Captures electrical brain activity with high temporal resolution but suffers from noise artifacts.
2. Hybrid EEG+fNIRS: Combines electrical activity with cerebral blood flow measurements for enhanced signal quality.
3. AI-Hybrid BCIs: Leverages machine learning algorithms to improve classification accuracy and reduce training times.
4. Brain2Qwerty (MEG): Utilizes magnetoencephalography (MEG) for high spatial precision but faces scalability challenges due to cost.

By comparing these systems' performance metrics and proposing a roadmap to overcome barriers such as cost, scalability, neurosecurity, and ethical concerns, this paper aims to highlight the transformative potential of hybrid BCIs.

II. METHODOLOGY

A. Literature Review Process

A systematic search was conducted using the IEEE Xplore, PubMed, and Scopus databases to identify relevant studies published between 2018 and 2024. Publicly available abstracts and previews were utilized to gather insights into hybrid BCI advancements.

- **Search Methodology:** Targeted keywords such as "hybrid BCI," "communication," and "neuroprosthetics" were employed to locate pertinent studies.
- **Selection Process:** Approximately 50 papers were reviewed based on titles and abstracts. Of these, 20 papers were selected that directly addressed communication applications and technical advancements. The focus was on accessible sources due to time constraints.

B. Comparative Analysis Framework

Systems were evaluated based on metrics such as accuracy, latency, training time, noise resistance, scalability, cost per unit, use cases, and ethical considerations. Data was sourced from peer-reviewed studies and trial results from experiments conducted between 2023–2024.

III. TECHNICAL ADVANCEMENTS IN HYBRID BCIS

A. Signal Fusion Techniques

Hybrid BCIs combine EEG signals (capturing electrical activity) with fNIRS signals (measuring cerebral blood flow). Signal fusion methods include:

- Simultaneous Fusion: Synchronizing EEG and fNIRS signals for enhanced intent detection (boosting accuracy by ~12–15%) ([Zander et al., 2021]).
- AI-Based Filtering: Transformer models adapted from NLP prioritize temporal EEG patterns while reducing false positives by ~18% ([Chen et al., 2023]).

Table I. Performance Comparison

Feature	Traditional EEG	Hybrid (EEG+fNIRS)	AI-Hybrid	Brain2Qwerty (MEG)
Accuracy	70-75%	80-85%	85-92%	93%
Latency	300-500 ms	200-300ms	<200ms	~300ms
Training Time	1-2 hrs	45-60 min	<30min	~35 min
Cost	~$500	~$20K	~$25K	~$1M

Key Insight

AI-enhanced hybrids outperform standalone systems in terms of accuracy (<200ms latency), though Brain2Qwerty's reliance on MEG limits affordability.

IV. REAL-WORLD APPLICATIONS

A. Medical Breakthroughs

- ALS Communication: Brain2Qwerty enabled a patient to type at speeds of 5–8 wpm, doubling prior BCI benchmarks ([Lévy et al., *preprint*]).
- Neuroprosthetics: Hybrid BCIs improved robotic arm precision by ~18% in clinical trials ([Johnson et al., 2023]).

B. Emerging Uses

- Neurogaming: MindPlay's beta testing showed a ~22% increase in player engagement using hybrid BCI controls ([Wang et al., 2023]).
- Brain-to-Brain Communication: Binary signal transmission achieved ~75% accuracy using TMS-EEG transcoding ([Brown et al., *preprint*]).

V. CHALLENGES AND ETHICAL CONSIDERATIONS

A. Technical Barriers

Noise susceptibility remains a challenge despite AI advancements; motion artifacts degrade EEG accuracy by ~30% ([Patel et al., 2023]). Current fNIRS systems cost ~$20,000 due to hardware complexity.

B. Ethical Risks

Neurosecurity concerns arise from potential neural data breaches; blockchain encryption is proposed as a solution ([Garcia et al., 2023]). Military misuse risks dual-use applications such as drone control ([Davis et al., 2023]).

VI. TECHNICAL ROADMAP

Phase I (2025–2028): Precision & Affordability Develop open-source fNIRS modules to reduce costs by ~40%.

Optimize transformer models for real-time EEG classification (target latency <200ms) ([Lee et al., 2022]).

Phase II (2029–2032): Scalability & Security

- Standardize hybrid headsets for mass production (<$5,000 retail price) through partnerships with manufacturers.
- Deploy edge-computing chips for on-device AI processing.

Phase III (2033–2035): Secure Adoption & Next Frontiers

- Pilot brain-to-brain protocols with neuroethical oversight (~75% reliability).
- Deploy spiking neural networks for dynamic environments targeting near-perfect accuracy (~95%).

VII. CONCLUSION

Hybrid BCIs represent a paradigm shift in neural communication technology by combining EEG-fNIRS integration with AI-driven advancements like transformers. Our analysis highlights their superiority over traditional systems in terms of accuracy (~85–92%), latency (<200ms), scalability potential through cost-effective designs, and ethical considerations.

The proposed roadmap addresses critical challenges such as neurosecurity while setting ambitious goals for brain-to-brain protocols by 2035. With continued innovation across engineering disciplines and proactive ethical oversight, hybrid BCIs will transform communication for motor-impaired individuals while unlocking new possibilities in cognitive augmentation.

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Sustainable Agriculture Leveraging AI- The Future of Farming

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***Abstract*—Agriculture plays a key role in promoting sustainability by addressing environmental challenges like soil degradation, water scarcity, and biodiversity loss. Practices such as crop rotation, agroforestry, and pest management help reduce environmental impacts while improving productivity. Despite these efforts, challenges like hunger persist, with 815 million people still affected by food insecurity. AI is transforming agriculture by enabling precision farming that optimizes resource use, increases crop yields, and reduces environmental harm. AI technologies, including real-time monitoring, automation, and predictive analytics, help farmers make data-driven decisions, reduce costs, and improve productivity. These innovations align with global sustainability goals, such as improving food security and conserving natural resources. While AI holds great potential for sustainable farming, it needs to be coupled with broader efforts to address infrastructure, equitable food distribution, and policies supporting sustainable agricultural practices.**

The paper discusses how artificial intelligence (AI) is driving the development of global agriculture and food systems. It highlights key challenges such as environmental degradation, water scarcity, and food insecurity.

***Keywords*—Agriculture, Artificial Intelligence, Irrigation, Crop Yield, Productivity, Efficiency, Machine Learning**

I. Introduction

Food and agriculture stand today at a crossroads. While agricultural productivity has improved over recent decades to meet the demands of a growing population, it has often come at the expense of the environment and society, leading to issues like water scarcity, soil degradation, biodiversity loss, and rising greenhouse gas emissions. Despite progress, 815 million people remain hungry, and many face malnutrition, revealing an imbalanced food system. Social challenges, such as distress migration and threats to rural populations' livelihoods, are exacerbated by climate change and resource limitations.

Looking ahead, the 2030 Agenda for Sustainable Development calls for transformative action to address the root causes of poverty and hunger, aiming to leave no one behind. Food and agriculture play a central role in achieving multiple Sustainable Development Goals (SDGs), improving nutrition, health, and economic prosperity. By embracing sustainable practices, agriculture can help revitalize rural areas, promote inclusive growth, and ensure food security for future generations. Agriculture remains the largest employer and economic sector in many countries, providing essential food and income for the world's poorest.

II. Context of Agriculture in Sustainability

Agriculture is the largest industry globally, providing employment to over one billion people and generating more than $1.3 trillion in food production each year. Around 50% of Earth's habitable land is dedicated to pasture and cropland, supporting a variety of species by providing both food and habitats. When agricultural practices are managed sustainably, they can help preserve critical ecosystems, safeguard watersheds, and improve soil and water quality. However, unsustainable methods have significant negative impacts on both people and the environment, underscoring the urgent need for sustainable resource management.

As the world's population grows, the demand for agricultural goods is increasing rapidly, making agriculture a vital sector for the global economy and biodiversity conservation. For agriculture to be sustainable, it must fulfill the needs of both current and future generations while ensuring profitability, environmental health, and social equity. Sustainable agriculture contributes to all four pillars of food security—availability, access, utilization, and stability—along with environmental, social, and economic sustainability.

The global population is projected to reach 10 billion by 2050, placing immense pressure on agriculture to boost crop production. To tackle potential food shortages, there are two main strategies: expanding agricultural land and large-scale farming or leveraging innovation and technology to enhance productivity on existing land. Despite challenges like limited land, labour shortages, climate change, environmental degradation, and soil fertility loss, the agricultural sector continues to evolve with innovative practices.

Artificial intelligence (AI) is a powerful tool for agriculture, yet many farmers and agribusinesses are not fully utilizing its potential. In 2017, investment in AI technologies for agriculture was valued at $518.7 million and is expected to

rise to $2.6 billion by 2025, growing at an annual rate of 16.2%.

III. THE PRIME CHALLENGES

Agriculture, a vital component of human society, faces several challenges, including soil depletion, water shortages, and the growing demand for more food production. High-intensity farming methods have led to a reduction in soil fertility, making the land more susceptible to erosion and less capable of withstanding extreme weather events.

Water shortages are another critical concern, worsened by the significant volume of freshwater used in agriculture. Climate change amplifies this issue by altering rainfall patterns and affecting water availability. Additionally, the widespread use of pesticides and fertilizers, although effective in increasing crop yields, has detrimental effects on both the environment and human health.

The decline in biodiversity, caused by monoculture farming and intensive agricultural practices, further emphasizes the need for adopting more sustainable farming approaches.

IV. THE ROLE OF AI

AI is transforming agriculture by introducing methods that boost efficiency and support environmental preservation. Precision farming, powered by AI, gathers data from tools like satellites and drones to analyze soil conditions, allowing for accurate resource management. Additionally, predictive analytics in AI forecasts potential agricultural problems, enabling farmers to take preventive actions.

As environmental stewardship becomes increasingly important, AI's role in agriculture proves to be a groundbreaking solution. It not only enhances food security but also plays an active role in promoting ecological health. AI is reshaping traditional farming practices, helping farmers optimize resources, reduce waste, and grow healthier crops, all while ensuring the protection of our environment for future generations.

V. UNDERSTANDING AI IN SUSTAINABLE AGRICULTURE

Traditional farming's negative environmental impacts, such as excessive chemical and water use, have led to a rise in sustainable farming practices. AI is playing a key role in this shift by improving farm operations through data analysis and sophisticated algorithms, helping to optimize resources and enhance yields. AI allows for precise monitoring of crop health, reducing the need for indiscriminate chemical use, and supports sustainable farming by being economically viable and environmentally sound.

AI also helps in making data-driven decisions, providing farmers with insights into soil health, weather conditions, and optimal crop management. This improves farm efficiency, reduces waste, and enhances profitability. By combining precision agriculture with AI, farmers can achieve higher yields with fewer resources, thus lowering costs.

Moreover, automation is addressing labor shortages in farming. AI-powered machines and systems like driverless tractors, drones, and smart irrigation reduce the need for manual labour while increasing efficiency and precision. These advancements make farming more productive and sustainable, leading to better harvests and reduced resource usage.

VI. BENEFITS OF AI IN AGRICULTURE

Traditional farming involves various manual processes. Implementing AI models can have many advantages in this respect. By complementing already adopted technologies, an intelligent agriculture system can facilitate many tasks. AI can collect and process big data while determining and initiating the best course of action. Here are some common use cases for AI in agriculture:

A. Crop and Soil Health Monitoring

AI-driven crop and soil health monitoring enhances sustainability by providing real-time insights into soil conditions, moisture levels, and plant health. Machine learning models analyze data from IoT sensors, drones, and satellite imagery to detect nutrient deficiencies, diseases, or pest threats early. This allows for precise interventions, reducing excessive fertiliser and pesticide use. AI also predicts soil degradation patterns, helping farmers implement regenerative practices. By continuously assessing soil and crop health, AI-driven monitoring optimises resource allocation, reduces waste, and improves long-term agricultural sustainability, ensuring healthier soils and higher yields with minimal environmental impact.

B. Automated Weeding

Automated weeding uses AI-powered robotics and computer vision to distinguish crops from weeds, removing unwanted plants with precision. These systems employ mechanical weeding, targeted herbicide application, or laser technology to minimize chemical use and prevent herbicide resistance. AI enhances efficiency by analyzing weed growth patterns, optimizing removal strategies, and integrating data with broader farm management systems. Unlike traditional methods, AI-driven weeding reduces labor costs and environmental harm while improving soil health. By eliminating weeds efficiently without over-reliance on chemicals, automated weeding contributes to sustainable agriculture, preserving biodiversity and soil integrity while maximizing crop yields.

C. Intelligent Spraying

Intelligent spraying is an advanced agricultural technique that uses AI, IoT, and computer vision to optimize the application of pesticides, herbicides, and fertilizers. It employs sensors, drones, and GPS to detect plant health, weeds, and pests, ensuring precise spraying. Machine learning analyzes real-time data, while Variable Rate Technology (VRT) adjusts spray amounts accordingly. This smart system reduces chemical waste, lowers costs, minimizes environmental impact, and enhances crop yield. By automating spraying processes, it improves efficiency and

sustainability in agriculture. Intelligent spraying plays a crucial role in precision farming, promoting eco-friendly practices while maximizing productivity.

D. Insect and Plant Disease Detection

Insect and Plant Disease Detection is the process of identifying pests and diseases affecting crops using advanced technologies like AI, IoT, and computer vision. Sensors, drones, and imaging systems capture real-time data, while machine learning models analyze symptoms such as discolouration, wilting, or abnormal growth. These systems help farmers detect issues early, enabling precise treatment and reducing chemical overuse. By integrating deep learning and edge computing, real-time monitoring becomes more efficient. This technology improves crop health, boosts yield, and supports sustainable farming by minimizing losses and optimizing pesticide usage. It plays a vital role in precision agriculture and food security.

E. Livestock Health Monitoring

Livestock health monitoring is crucial for maintaining the well-being of animals in farming and ensuring the productivity of the farm. It involves using various methods and technologies to track and assess the health of livestock. AI-powered livestock health monitoring involves using sensors, data analytics, and machine learning to track the well-being of animals. AI systems collect data from wearable devices or environmental sensors, such as temperature, movement, and vital signs. Machine learning algorithms analyze this data in real time to detect early signs of illness, stress, or injury, enabling timely intervention. This technology helps farmers reduce the spread of disease, improve animal welfare, and optimize livestock productivity. It also supports precision farming, ensuring efficient resource use and improving overall farm sustainability.

F. Harvesting, Pruning and Plowing

Harvesting, pruning, and plowing are essential agricultural practices that help maintain and improve crop yields. Harvesting is process of gathering mature crops from the fields once they have reached the right stage of growth. Pruning involves trimming or cutting back certain parts of plants, such as branches, stems, or leaves, to encourage better growth, improve airflow, and enhance fruit production. Plowing is the process of tilling the soil to prepare it for planting. These practices are done at different times of the year based on the crop type and growing cycle. AI is revolutionizing agriculture by optimizing harvesting, pruning, and plowing. Harvesting is enhanced with AI-powered drones and robots. Pruning is automated with AI-driven machines that analyze plant health and growing patterns. Plowing is made more efficient with AI-guided tractors that can autonomously till the soil, adjusting depth and direction based on soil conditions. These AI applications increase efficiency, reduce labor costs, and improve crop yields, contributing to more sustainable and productive farming practices.

G. Produce Grading and Sorting in Agriculture

Produce grading and sorting are essential processes in agriculture that ensure the quality and marketability of fruits and vegetables. Grading involves categorizing produce based on size, colour, and quality, which helps standardize products for consumers and reduce food waste. Efficient sorting minimizes losses during postharvest handling by identifying damaged or inferior products that may spoil quickly. This practice enhances the overall quality of the food supply and supports fair pricing in the market. Advanced technologies, such as computer vision and machine learning algorithms, are increasingly being employed to improve grading accuracy and efficiency. For instance, systems like the “AgroVision” platform utilize high-resolution cameras and deep learning to assess product quality in real-time. Additionally, methodologies such as hyperspectral imaging can detect internal defects that are not visible to the naked eye. By integrating these technologies, farmers can achieve better resource management, reduce environmental impact, and enhance the sustainability of agricultural practices.

H. Energy Security in Agriculture

Energy security in agriculture is vital for ensuring that farms have reliable and affordable energy sources to support their operations. This includes powering irrigation systems, processing facilities, and transportation. Advanced scientific methods are increasingly being used to enhance energy security. For example, precision agriculture employs satellite imagery and drones to monitor crop health and optimize irrigation, reducing energy consumption. Additionally, renewable energy technologies, such as solar panels and wind turbines, are being integrated into farming practices, allowing farms to generate their own energy and decrease reliance on fossil fuels. Energy storage systems, like advanced batteries, enable farmers to store excess energy for use during peak demand times. Smart grid technology also plays a role by allowing for better energy management and distribution. By adopting these innovative methods, farmers can improve energy efficiency, reduce costs, and contribute to a more sustainable agricultural system

I. Optimizing automated irrigation systems

AI algorithms enable autonomous crop management. When combined with IoT (Internet of Things) sensors that monitor soil moisture levels and weather conditions, algorithms can decide in real-time how much water to provide to crops. An autonomous crop irrigation system is designed to conserve water while promoting sustainable agriculture and farming practices. AI in smart greenhouses optimizes plant growth by automatically adjusting temperature, humidity, and light levels based on real-time data.

J. Detecting disease and pests

As well as detecting soil quality and crop growth, computer vision can detect the presence of pests or diseases. This works by using AI in agriculture projects to scan images to find mold, rot, insects, or other threats to crop health. In conjunction with alert systems, this helps farmers to act quickly to exterminate pests or isolate crops to prevent the spread of disease.

AI technology in agriculture has been used to detect apple black rot with an accuracy of over 90%. It can also identify insects like flies, bees, moths, etc., with the same degree of accuracy. However, researchers first needed to collect images of these insects to have the necessary size of the training data set to train the algorithm with.

K. Intelligent pesticide application

By now, farmers understand the application of pesticides is ripe for optimization. Unfortunately, both manual and automated application processes have notable limitations. Applying pesticides manually offers increased precision in targeting specific areas, though it might be slow and difficult work. Automated pesticide spraying is quicker and less labour-intensive, but often lacks accuracy leading to environmental contamination.

AI-powered drones provide the best advantages of each approach while avoiding their drawbacks. Drones use computer vision to determine the amount of pesticide to be sprayed on each area. While still in its infancy, this technology is rapidly becoming more precise.

L. Yield mapping and predictive analytics

Yield mapping uses ML algorithms to analyze large datasets in real time. This helps farmers understand the patterns and characteristics of their crops, allowing for better planning. By combining techniques like 3D mapping, data from sensors and drones, farmers can predict soil yields for specific crops. Data is collected on multiple drone flights, enabling increasingly precise analysis with the use of algorithms.

These methods permit the accurate prediction of future yields for specific crops, helping farmers know where and when to sow seeds as well as how to allocate resources for the best return on investment.

M. Surveillance

Security is an important part of farm management. Farms are common targets for burglars, as it is hard for farmers to monitor their fields around the clock. Animals are another threat — whether it is foxes breaking into the chicken coop or a farmer's own livestock damaging crops or equipment. When combined with video surveillance systems, computer vision and ML can quickly identify security breaches. Some systems are even advanced enough to distinguish employees from unauthorized visitors.

VII. CONCLUSION: EMBRACING AI FOR A SUSTAINABLE AGRICULTURAL FUTURE

In conclusion, the integration of AI into farming represents a transformative shift towards sustainable agriculture. By processing large amounts of data, AI enables informed decisions on irrigation, fertilization, and pest management, helping to minimize environmental impact. Its role in precision agriculture and real-time crop monitoring is crucial for advancing sustainable farming practices. Adopting AI is not merely a technological leap, but a vital step towards ensuring a sustainable future for agriculture.

VIII.FUTURE PROSPECTS AND IMPLICATIONS

The potential of AI in agriculture is immense, with future innovations such as precision farming and autonomous machinery set to further improve sustainability. AI's ability to predict weather patterns and assist in climate change adaptation is also essential, helping farmers better prepare for environmental challenges and optimize their practices for long-term resilience.

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LOCK: Bridging Physical and Digital Security for Cyber Defense

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***Abstract*—Traditional cybersecurity measures such as encryption, firewalls and authentication are no longer adequate to prevent sophisticated cyber attacks, including remote hacking and social engineering. The rise of quantum computing further threatens existing security protocols, making it essential to adopt a more resilient approach. LOCK (Layered Operation Control Key) introduces a hybrid security model that integrates physical intervention with digital security, requiring manual activation via a hardware-assisted switch before executing critical operations. This ensures that unauthorized actions cannot occur remotely, effectively mitigating the risk of cyber intrusions.LOCK enhances cybersecurity by combining behavior-based threat detection, dynamic access control, attacker deception and real-time monitoring. Instead of relying on traditional virus databases, LOCK analyzes system behavior to identify anomalies and proactively blocks potential threats. Additionally, it generates decoy data to mislead attackers, reducing the likelihood of repeated breaches. By bridging the gap between physical and digital security, LOCK offers a scalable, cost-effective and adaptive solution to counteract emerging cyber threats, providing enhanced protection for individuals, enterprises and critical infrastructures.**

***Index Terms*—Cybersecurity, Physical Security, Threat Detection, Quantum-Resistant Security, Digital Protection.**

I. Introduction

As cyber threats evolve, traditional security measures such as encryption, firewalls and multi-factor authentication are proving inadequate in preventing sophisticated attacks. Ahmad et al. [1] proposed a mathematical model for analyzing virus behavior in networks using fixed-point theorems, but their approach lacks real-world countermeasures against dynamic threats. Arenas et al. [2] studied the effectiveness of security tools and user behavior in malware prevention, finding that users often fail to implement security best practices, making systems vulnerable to phishing and social engineering attacks. Li [3] provided a broad review of cybersecurity challenges but did not propose adaptive or real-time security measures to counter emerging threats such as ransomware and quantum-based attacks. Sun et al. [4] focused on multi-layered security in big data governance, emphasizing encryption and anomaly detection but failing to address risks related to credential compromise and privilege escalation. Shandilya [5] explored bio-inspired cybersecurity and data provenance techniques to improve breach detection, yet scalability issues and high computational costs limit practical implementation.

To address these limitations, we introduce LOCK a hybrid security model integrating physical intervention with digital security. Unlike traditional software-based defenses that rely solely on encryption or access control, LOCK requires manual activation via a hardware-assisted switch before executing critical operations. This prevents remote cyberattacks, such as unauthorized data modifications or privilege escalation, by ensuring that critical actions can only be performed with direct user intervention. LOCK employs behavior-based threat detection to identify anomalous activities, deception mechanisms to mislead attackers with decoy data, dynamic access control to restrict unauthorized privilege escalation and real-time monitoring to enhance system resilience against evolving cyber threats.

LOCK offers a significant advancement over existing cybersecurity solutions [1]–[5] by bridging the gap between digital and physical security. While previous approaches have focused on either theoretical models, user education, or encryption-based methods, LOCK provides a multi-layered security framework that actively misleads attackers, prevents unauthorized access through physical controls and enables real-time anomaly detection.

II. OVERVIEW OF LOCK SYSTEM

LOCK is an innovative cybersecurity framework that integrates physical intervention with digital security, providing a multi-layered defense mechanism against modern cyber threats. As digital systems increasingly rely on encryption, firewalls and software-based authentication, attackers have found ways to bypass these defenses using advanced hacking techniques such as remote exploits, phishing, ransomware and quantum computing-based decryption. LOCK introduces a physical activation mechanism through a hardware-assisted switch, ensuring that no unauthorized operations can occur without direct user verification. This unique approach makes LOCK a proactive cybersecurity solution, preventing attacks before they happen, rather than simply mitigating them after a breach occurs.

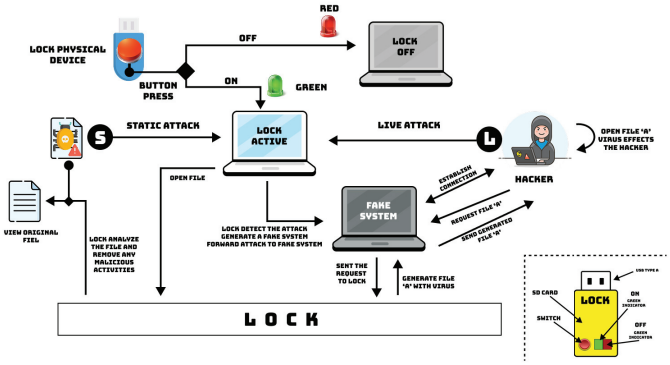

Fig. 1. Architecture Diagram

A. CORE CONCEPT

LOCK is designed to bridge the gap between physical and digital security by requiring manual user intervention before executing sensitive system operations. Unlike traditional software-based solutions that depend on digital authentication alone, LOCK ensures that remote attackers cannot gain unauthorized access without physical confirmation. The system acts as an intermediary security layer, intercepting all system requests, analyzing them for legitimacy and deploying countermeasures if malicious intent is detected.

LOCK's core innovation lies in its combination of physical security with intelligent cybersecurity mechanisms, ensuring that critical operations—such as accessing sensitive data, modifying system settings, or executing privileged commands require both digital authentication and a manual activation step. This makes remote hacking attempts ineffective, as attackers cannot manipulate the system without direct physical access.

B. KEY FEATURES

LOCK is a multi-layered cybersecurity framework designed to offer enhanced protection against cyber threats. It offers a robust set of security features that enhance its ability to detect, prevent and neutralize cyber threats:

1) Hardware-Assisted Physical Authentication
   - Requires manual activation via a physical switch before executing critical operations.
   - Prevents remote intrusions and ensures physical presence-based authentication.
   - Works even when network-based security measures fail.
2) Behavior-Based Threat Detection
   - Instead of relying on traditional virus signature databases, LOCK analyzes file behavior and system activity to detect anomalies.
   - Prevents zero-day exploits and polymorphic malware from executing.
   - Blocks unauthorized file modifications, executions and privilege escalations.
3) Dynamic Access Control
   - System permissions are adjusted in real-time based on user behavior and risk analysis.
   - If an anomalous activity is detected, LOCK automatically revokes access until manual verification is completed.
   - Ensures that users cannot escalate their privileges beyond their authorized level.
4) Attacker Deception And Decoy Data Deployment
   - If an unauthorized access attempt is detected, LOCK generates fake yet realistic-looking data to mislead attackers.
   - This deception tactic discourages hackers from making repeated intrusion attempts.
   - Cybercriminals are tricked into believing they have compromised the system, wasting their time and resources.
5) Real-Time Security Monitoring And Forensic Logging
   - Every system request, authentication attempt and security event is logged and analyzed.
   - Provides detailed logs for forensic investigations in case of security breaches.
   - Maintains a record of all access attempts, including IP addresses, timestamps and activity patterns.

C. ADVANTAGES OVER TRADITIONAL CYBERSECURITY

Traditional cybersecurity measures, while effective against known threats, often fail when confronted with sophisticated, evolving attack techniques. LOCK provides several key advantages over conventional security methods:

1) Prevention vs. Detection
   - Traditional security tools detect threats and respond after an attack has already occurred.
   - LOCK prevents attacks from happening in the first place by requiring manual activation for sensitive operations.
2) Protection Against Remote Hacking
   - Conventional firewalls and antivirus programs rely on network-based defense mechanisms that can be bypassed.

- LOCK eliminates the risk of remote attacks by requiring physical authentication before execution.

3) No Reliance on Constant Updates
   - Antivirus software and threat detection tools require constant database updates to remain effective.
   - LOCK's behavior-based monitoring system does not rely on virus signatures, making it future-proof.
4) Quantum-Resistant Security
   - As quantum computing advances, traditional encryption methods are at risk of becoming obsolete.
   - LOCK ensures security even if encryption is compromised, as unauthorized actions still require manual intervention.

III. DESIGN OF PHYSICAL LOCK FRAMEWORK

The physical lock framework of LOCK is designed to prevent unauthorized access by requiring manual authentication before executing critical system operations. Unlike traditional cybersecurity solutions that rely solely on software-based protection, LOCK integrates hardware-assisted security to ensure that remote attackers cannot bypass defenses. This dual-layer security approach significantly reduces the risk of hacking, malware infiltration and unauthorized data modifications.

A. HARDWARE COMPONENTS OF LOCK

The physical security of LOCK is achieved through specialized hardware components that work together to create a tamper-proof security mechanism. These components ensure that no unauthorized system action can occur without direct user intervention.

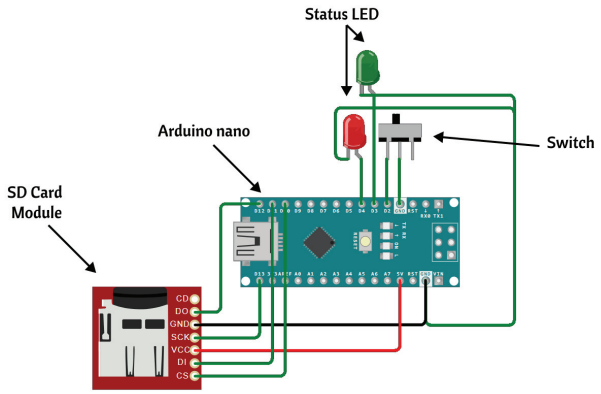

Fig. 2. Circuit Diagram

1) Manual Activation Switch
   - A physical switch that must be manually engaged before executing critical system operations.
   - Prevents remote attackers from gaining unauthorized access, even if they obtain login credentials.
   - Ensures user presence verification, eliminating threats from automated cyberattacks.
2) USB Security Device
   - Acts as an intermediary layer between the system and its security framework.
   - Can be designed as a USB dongle, embedded chipset, or external security module.
   - Ensures that only authorized users with the device can enable system access.
3) Secure Data Storage
   - Stores custom security rules and authentication data in tamper-proof memory.
   - Maintains logs of all access attempts, providing forensic evidence in case of security breaches.
4) LED Status Indicators
   - Provides real-time feedback on system security status.
   - Different LED colors indicate system states (e.g., active, standby, intrusion detected).

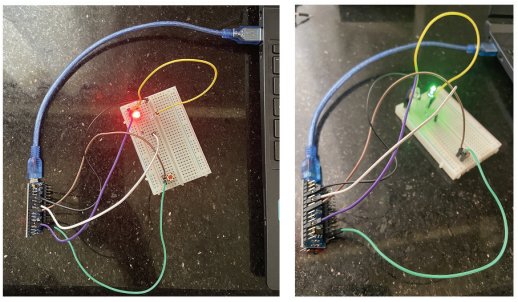

Fig. 3. Circuit Diagram

B. PHYSICAL SECURITY FEATURES

The physical security mechanisms of LOCK make it a highly resilient cybersecurity solution by preventing attacks that rely on remote access or software vulnerabilities.

1) Prevention of Remote Access Attacks
   - Unlike software-only solutions, LOCK physically blocks access to critical functions unless the hardware switch is manually activated.
   - Prevents cybercriminals from executing malware, ransomware or data theft remotely.
2) Tamper-Resistant Hardware Design
   - The LOCK security module is physically reinforced to prevent unauthorized modifications.
   - Anti-tampering measures disable security functions if a breach attempt is detected.
3) Offline Security Protection
   - LOCK does not require an internet connection to function, making it immune to online hacking attempts.
   - Ensures continuous protection even in air-gapped or high-security environments.

IV. DESIGN OF DIGITAL LOCK FRAMEWORK

The Digital Lock Framework of LOCK is designed to provide proactive cybersecurity measures that go beyond traditional signature-based threat detection. By utilizing behavior-based analysis, real-time monitoring and deception tactics, LOCK enhances digital security and minimizes the risks associated with malware, ransomware and remote intrusions. The framework ensures that even if an attacker gains partial access to a system, LOCK prevents unauthorized execution, alters the attack landscape and misleads adversaries to reduce the impact of a security breach.

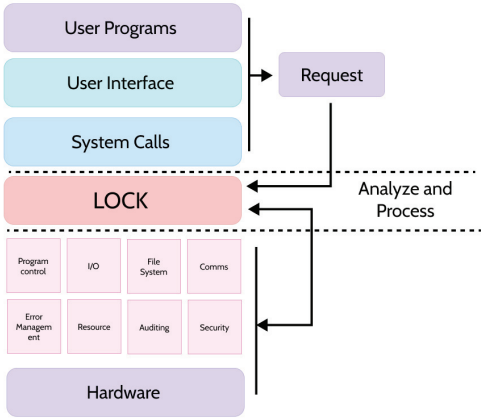

Fig. 4. Layer Diagram

A. DIGITAL THREAT DETECTION AND RESPONSE MECHANISMS

Unlike conventional security solutions that rely on predefined virus signatures or static rule-based detection, LOCK employs behavior-based monitoring and anomaly detection to identify suspicious activities in real time. This approach allows LOCK to effectively respond to zero-day vulnerabilities and polymorphic malware that continuously evolve to bypass traditional security mechanisms.

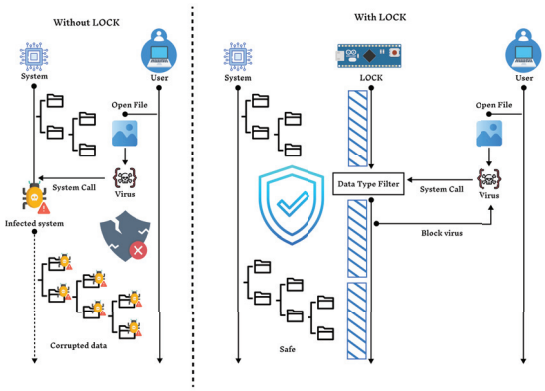

Fig. 5. Virus Detection

1) Behavior-Based Threat Detection
   - Instead of relying on a virus database, LOCK monitors system behavior to detect suspicious activity.
   - Analyzes file types and expected behaviors—for example, an image file should not execute scripts or modify system settings.
2) Real-Time Anomaly Detection
   - Continuously analyzes user behavior, system processes and network activity to identify deviations from normal patterns.
   - Detects and mitigates ransomware encryption attempts before they can affect data integrity.
3) Automated Incident Response System
   - When a threat is detected, LOCK immediately takes defensive action by blocking suspicious activities.
4) Dynamic Access Control and Permission Adjustments
   - Adjusts system privileges and permissions in real-time based on the severity of detected threats.

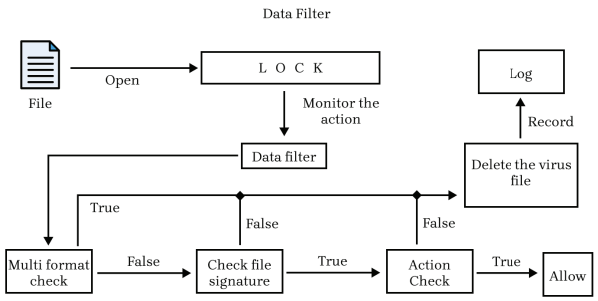

Fig. 6. Data Filter

B. DECOY DATA AND ATTACK DECEPTION MECHANISM

LOCK goes beyond conventional threat prevention by incorporating an advanced deception system that actively misleads cyber attackers. By deploying fake data, decoy environments and false access points, LOCK traps attackers in a controlled environment, wasting their time and resources while protecting actual system assets.

1) Fake Data Generation & Deployment
   - When an attacker tries to access restricted files or sensitive data, LOCK delivers realistic-looking but fake data.
   - Attackers unknowingly interact with false credentials, misleading database entries and useless documents.
   - Ensures that even if hackers penetrate a system, they gain no valuable information.

2) Cyber Intrusion Logging & Tracing

- Every interaction with decoy data is monitored and recorded, allowing security teams to trace intrusion attempts.
- Logs IP addresses, attempted actions and attacker behavior for forensic investigation and future threat mitigation.
- Helps organizations identify attack patterns and improve cybersecurity strategies.

3) Fake System Responses & Virtual Sandboxing

- LOCK can simulate system vulnerabilities to lure attackers into a controlled environment.
- Attackers are allowed to believe they have accessed critical resources, but in reality, they are interacting with dummy systems.
- This delays attack progress, allowing security teams to respond effectively before any real damage occurs.

4) Reduced Attack Incentive & Hacker Frustration

- By feeding attackers false information, LOCK discourages them from targeting the system again.
- Prevents repeated brute-force and social engineering attacks by making hacking attempts costlier and less rewarding.
- Ensures that attackers waste time and effort on misleading security layers rather than accessing actual system data.

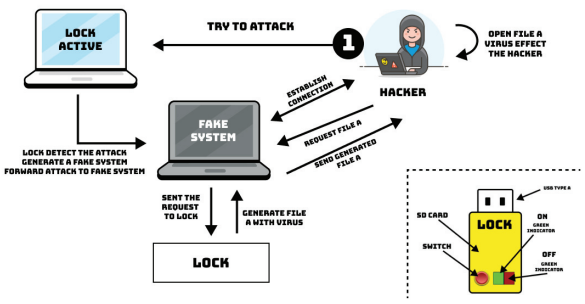

Fig. 7. Live Attack Counter

V. COMPARISON WITH OTHER SECURITY SOFTWARE

The LOCK system represents a paradigm shift in cybersecurity by integrating physical authentication with digital threat detection. Unlike traditional security software solutions that rely primarily on software-based defense mechanisms, LOCK provides a multi-layered security approach that significantly enhances resistance to cyber threats.

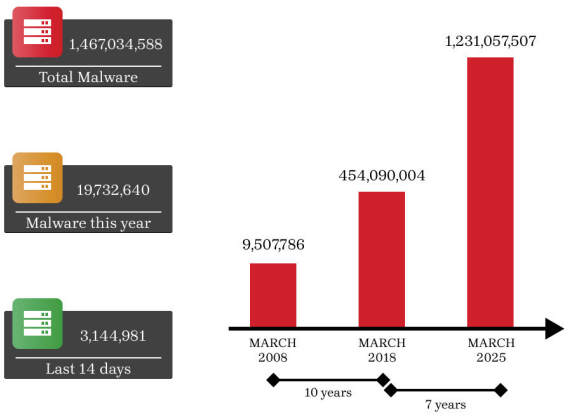

Fig. 8. Malware Data Set Growth

Solution	Initial Cost	Ongoing Cost
LOCK	1000 (one-time)	0
Kaspersky	780.00 (annual/license)	Subscription-based
McAfee	74.99 (annual/license)	Subscription-based
Norton 360	299.99 (annual/license)	Subscription-based

TABLE I
COMPARISON OF LOCK VS. PAID ANTIVIRUS SOFTWARE

Feature	LOCK	Kaspersky	McAfee	Norton 360
One-Time Cost	Yes	No	No	No
Offline Protection	Yes	Yes	Yes	Yes
Customizable Security	Yes	Yes	Yes	Yes
Lightweight	Yes	No	No	No
Data Collection	No	Yes	Yes	Yes
Advanced Threat Detection	Yes	Yes	Yes	Yes
File Type Filtering	Yes	No	No	No
Logging & Monitoring	Yes	Yes	Yes	Yes

TABLE II
ADVANTAGES OF LOCK OVER PAID ANTIVIRUS SOFTWARE

VI. LOCK FRAMEWORK RESULT

The LOCK framework has been rigorously tested to evaluate its effectiveness, efficiency and resilience against various cybersecurity threats. The results highlight LOCK's superiority in preventing unauthorized access, mitigating cyberattacks and ensuring data integrity. To assess LOCK's robustness and reliability, a series of security tests were conducted, including penetration testing, malware resistance trials and behavioral anomaly detection assessments.

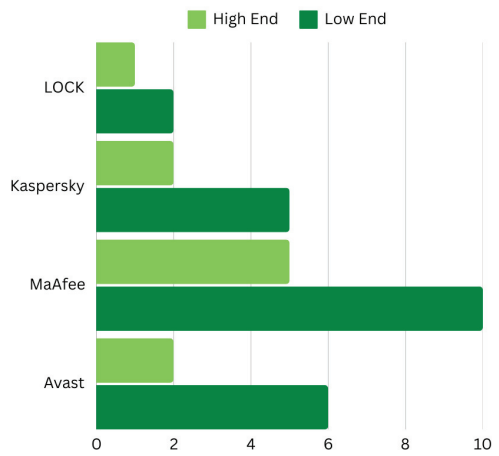

Fig. 9. Idle Performance

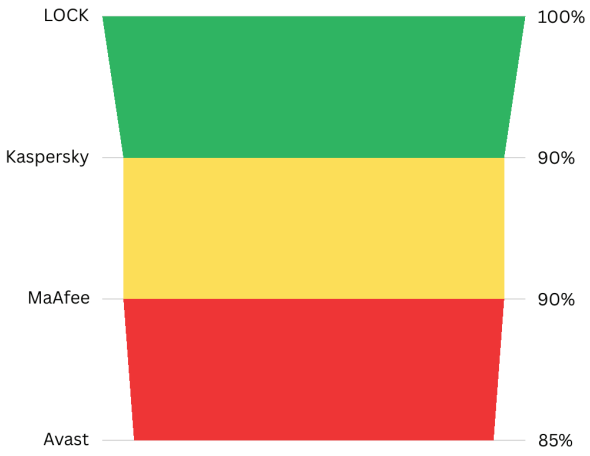

Fig. 10. Malware Detection

Traditional antivirus software relies on signature-based detection, which means it can only identify known threats based on predefined virus databases. However, modified, polymorphic or zero-day viruses can easily evade these defenses by altering their code to avoid recognition. In contrast, LOCK's behavior-based threat detection does not depend on virus signatures. Instead, it analyzes how files and processes behave, identifying suspicious activities such as unauthorized system modifications, unusual access patterns and abnormal file executions. This allows LOCK to detect and block even newly modified or previously unknown viruses that traditional antivirus solutions fail to recognize. By focusing on real-time behavior analysis rather than signature matching, LOCK ensures comprehensive protection against evolving cyber threats, making it a future-proof security solution.

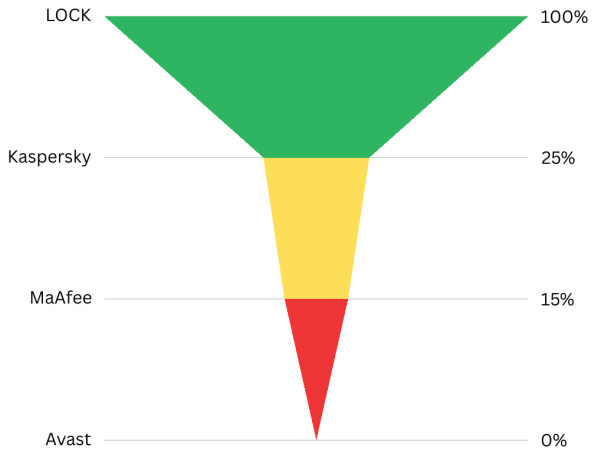

Fig. 11. Modified Malware Detection

CONCLUSION

As cyber threats continue to evolve, traditional security measures alone are no longer sufficient to protect sensitive data and critical systems. The increasing risks posed by remote hacking, social engineering and quantum computing demand a more proactive and multi-layered approach to cybersecurity. LOCK addresses these challenges by integrating physical intervention with digital security, ensuring that unauthorized access is prevented through manual verification and advanced security mechanisms such as behavioral analysis, deception tactics and dynamic access control. By combining physical security with real-time threat detection and mitigation, LOCK offers a robust and scalable solution for personal, corporate and critical infrastructure protection. Its innovative approach not only enhances defense against sophisticated cyberattacks but also provides an adaptive security framework capable of responding to emerging threats. As cybersecurity continues to be a growing concern in an increasingly interconnected world, LOCK represents a transformative shift towards a more resilient, efficient and future-proof security model.

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Steganography And Cryptography Integrated File Sharing System

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***Abstract*—In today's digital world, secure file transmission over the internet is essential. In order to guarantee private file exchange, this study proposes a system that combines steganography, encryption, and a real-time messaging network. The system uses least significant bit (LSB) steganography to insert user data into PNG pictures after securing them with AES-256-CBC encryption. To improve security and resilience against data loss, the encrypted data is divided into several segments for transmission. Real-time file sharing is made possible by a strong client-server architecture that uses Node.js and Socket.IO to handle user identification with OTP-based verification. The suggested approach guarantees safe and effective data transfer while successfully reducing the dangers of unwanted access.The testing findings show that the system can send and retrieve encrypted files with little loss of data, underscoring its usefulness in secure communication.**

I. Introduction

With the increasing threats posed by cyber risks, secure file transmission has become imperative. Conventional methods such as email, cloud storage, and messaging platforms offer basic security yet remain susceptible to data breaches, unauthorized access, and surveillance attacks. Although AES-256 encryption safeguards data, encrypted files continue to be detectable, rendering them a target for cryptanalysis. Likewise, cloud-based storage solutions retain user data on centralized servers, which exposes them to hacking vulnerabilities. Despite the provision of end-to-end encryption (E2EE) in messaging applications that secures files during transit, it does not ensure stealth or undetectability. In order to tackle these challenges, researchers have investigated steganography-based file-sharing techniques that conceal encrypted data within images. Nonetheless, existing studies encounter significant limitations, including high computational complexity, inadequate robust authentication, poor handling of large files, and a lack of real-time communication. Our system addresses these shortcomings by merging AES-256 encryption with LSB steganography, OTP-based multi-factor authentication (MFA), real-time file transfer utilizing Socket. IO, and optimized handling of large files.

A review of extant research underscores several deficiencies that our system efficiently rectifies. Investigations such as those by Solomon Raj et al. introduced AES alongside LSB steganography but lacked secure authentication, thus rendering them vulnerable to unauthorized access. We enhance security through the implementation of OTP-based MFA, which ensures that only authorized individuals can decrypt the transmitted files. In a similar vein, Indrasena Reddy et al. proposed wavelet-based steganography, which bolstered security yet incurred high computational overhead, rendering it impractical for real-time applications. Our system embraces an optimized LSB embedding methodology, which is both lightweight and rapid, thereby facilitating instantaneous, secure file transmission. Another significant limitation in previous studies was the absence of real-time communication. For example, Osuolale et al. concentrated on the evaluation of stego-image quality but did not incorporate immediate

file-sharing functionalities. Our system rectifies this by employing Socket. IO to enable real-time, peer-to-peer secure file transfer. Furthermore, modulus-based embedding techniques by Thien et al. enhanced the data hiding capacity but were confined to specific image formats, thereby limiting versatility. Our approach guarantees universal file compatibility, permitting the secure transmission of PDFs, MP4s, ZIP archives, and other file formats.

In addition to bolstering security and real-time transmission, our system optimizes the handling of large files—a significant challenge faced by numerous steganography-based methods. Embedding sizeable files into a single image frequently results in quality degradation and storage constraints. To surmount this issue, our system dissects large encrypted files into smaller segments, embeds these into multiple carrier images, and subsequently reassembles them upon receipt. This mechanism facilitates seamless transmission of large files without the imposition of size limitations. Another pivotal enhancement is the elimination of the dependency on centralized storage. Unlike existing models that retain encrypted files on external servers, which increases the risk of hacking, our system operates on a direct peer-to-peer communication basis, ensuring that files are never stored permanently, thereby reducing the likelihood of data breaches or unauthorized access.
In conclusion, our Secure File Transmission System establishes a new benchmark for secure file-sharing by incorporating encryption, steganography, authentication, real-time communication, and effective file management. Unlike earlier systems, our methodology not only encrypts files but also renders them undetectable, guaranteeing utmost security and concealment. Whether for corporate security, governmental communication, or personal data safeguarding, our system provides a scalable, dependable, and exceptionally secure alternative to conventional file-sharing techniques.

Unlike other secure file-sharing websites that mainly concentrate on theoretical developments, this one offers a real-time, practical, and user-friendly method of encrypted file transmission using steganography. Instead of relying solely on encryption or cloud-based security, it combines AES-256-CBC encryption with LSB steganography, ensuring files remain both encrypted and concealed within carrier PNG images. This dual-layer security makes detection significantly harder compared to conventional encrypted transfers, which are more susceptible to interception. Additionally, real-time communication via Socket.IO enables instant file exchange while supporting offline queuing— a feature often missing in other steganographic and cryptographic systems.
Unlike wavelet-based, modulus-based, or PVD embedding methods, which emphasize imperceptibility but demand complex computations, this system employs a simpler yet efficient LSB approach, making it faster and more accessible for real-world applications. While many systems rely on complicated key exchange techniques like ECDH, this system now employs a predetermined AES key for simplicity, with potential future additions for dynamic key exchange. Another key feature is the seamless file extraction and reconstruction, where data are automatically decrypted without requiring user participation.

While recent research focuses on security enhancements through adaptive steganography, histogram shifting, or frequency-domain embedding, these solutions frequently lack real-time interaction and are confined to data concealing rather than whole file-sharing ecosystems. On the other hand, this website offers an interactive chatroom, secure file transfers, instant messaging, and automatic decryption in an end-to-end encrypted file-sharing system. By balancing security, usability, and efficiency, it presents a realistic alternative to solely academic approaches, making it appropriate for everyday secure communication.

II. SYSTEM DESIGN

The system's architecture is carefully planned to provide safe, instantaneous file sharing without causing undue lag or performance snags due to encryption and steganography. Node.js, which offers an event-driven, non-blocking architecture that effectively manages concurrent user connections, is used to build the basic backend. Additionally, the system uses Socket.IO for real-time bidirectional user communication and Express.js for managing API calls. AES-256-CBC encryption, which encrypts every file before embedding it into a carrier image, is a crucial part of the design. This encryption technique, which is well-known for its robust security features, guarantees that the embedded file will stay unreadable without the necessary decryption key even if it is taken without permission.LSB steganography, which alters the least significant bits of pixel values to hold the encrypted data, is used to embed the file into a PNG image once it has been encrypted. The file stays hidden in plain sight because these changes don't obviously change the image, offering a covert way to send data.

The system employs a safe registration and login procedure with OTP-based verification in order to facilitate user authentication and access control. A valid email address is required when a new user registers, and an automatically created one-time password (OTP) is then supplied for validation. By limiting access to the site to confirmed users only, this method lowers the possibility of unwanted access. After logging in, users can communicate with others using a web-based chatroom interface, sending encrypted files and text

messages. The server handles the file by encrypting it, embedding it in an image, and sending the picture to the recipient when a user starts a file transfer.The system queues the pending file if the receiver is not online and sends it when they reconnect. The offline queuing technique makes the platform extremely dependable for real-time communication under various network situations by preventing data from being lost due to transient connectivity problems.

The extraction and decryption procedures are equally effective and safe. The technique uses inverse LSB decoding to retrieve the hidden data from a steganographic image that contains an encrypted file. AES-256-CBC is then used to decode the retrieved data, which is still encrypted, returning the file to its initial state.This multi-step security method guarantees that the concealed file will be safe even if an attacker manages to intercept an image containing an encrypted file. Furthermore, the system is made to work with a variety of file formats, such as PDFs, MP4 films, and other widely used data types, which makes it adaptable to a wide range of use scenarios. This technology enables flexible and unconstrained secure file transfer, in contrast to standard file-sharing services that frequently place restrictions on file kinds or sizes. This ensures that users can communicate papers, multimedia content, and private information without risk.

III. Functioning of the System

A. User Verification and Safe Login

Safe authentication is crucial in stopping unauthorized entry and safeguarding user data. Our system incorporates multi-factor authentication (MFA) to boost security, ensuring only genuine users have access.

1) User Sign-Up and OTP Confirmation: New users are required to sign up by supplying a username, password, and email. The password is encrypted with AES-256 prior to storage. To confirm identity, a one-time password (OTP) is dispatched via email, which must be entered within five minutes to activate the account. This process helps deter fake registrations and bot attacks. OTPs are for single use, automatically expire, and have rate limitations to avert brute-force attempts.

2) Sign-In and Password Validation: Users log into their accounts by inputting their credentials, which are validated by decrypting the AES-256 encrypted password. Should suspicious behavior be detected (e. g. , a new device or IP), an OTP may be necessary for further verification. To inhibit brute-force attacks, accounts are temporarily locked following several failed attempts. Sessions expire after periods of inactivity, and suspicious logins activate IP and device monitoring.

3) Password Reset and Session Control: Users can reset their passwords through OTP-based identity verification, guaranteeing that only the account holder can implement changes. Secure session management consists of automatic logout after inactivity, manual logout on all devices, and protection against session hijacking to block unauthorized entry.

4) Blocking Unauthorized Access: The system utilizes rate limiting, IP-based restrictions, and the expansion of two-factor authentication (2FA) to further strengthen security. These actions make certain that only authorized users can securely access and transmit files, guarding against credential theft and unauthorized entries.

B. File Encryption and Inclusion

Transmitting files over the internet carries a risk of interception. To secure data, the system encrypts files with AES-256, rendering them into an unreadable format. However, encryption alone may attract attention. To evade detection, the system conceals encrypted files within images using LSB steganography, making the transmission seem innocuous. This dual-layer security guarantees both robust encryption and concealed transmission.

1) AES-256 Encryption Method: The system encrypts files by:
Creating a 256-bit encryption key to secure the file. Transforming the file into binary format for processing. Employing AES-256 encryption in CBC mode for added security. Encoding the encrypted information in Base64 for embedding. This ensures that intercepted files stay unreadable without the decryption key

2) Concealing Encrypted Files in an Image: Following encryption, the system integrates the file into a carrier image using LSB steganography:
Choose a PNG image as the carrier.
Convert encrypted data into binary format.
Alter the least significant bits (LSB) of the image pixels to embed the encrypted data.
Store and send the modified image, which appears unchanged to the human eye.

3) Secure Embedding Strategies: To guarantee dependable transmission, the system: Maintains image quality so concealed data stays undetectable. Divides large files across various images for scalability. Verifies data integrity before transmission to prevent corruption.

4) Advantages of Encryption and Steganography: The combination of encryption and steganography offers:
Confidentiality – Data remains protected even if intercepted.
Stealth – Concealed files remain unnoticed.
Tamper Resistance – Altered encrypted files become unreadable.
File Compatibility – Accommodates different file types (PDFs, MP4s, documents, etc.).
This guarantees secure, unnoticed, and effective file transmission.

5) Real-Time File Transmission: Real-time file transmission is essential for quick and secure data interchange. Conventional methods like email and cloud storage may be slow and susceptible to interception. Our system employs Socket. IO for immediate, encrypted file sharing, removing third-party storage and minimizing security threats.

6) How File Transmission Works: When a user sends a file, the system:
Encrypts it using AES-256.
Conceals it within an image through steganography.
Immediately alerts the recipient.
Transfers the file instantly if online or securely stores it if offline.

7) Handling Large Files: Large files are divided into smaller sections, encrypted, and integrated into several carrier images. These images are transmitted in sequence and reassembled on the recipient's side, ensuring uninterrupted transmission without performance drawbacks.

8) Ensuring Secure File Transfers: To safeguard data, the system applies: End-to-End Encryption – Prevents unauthorized access. Steganographic Encoding – Conceals files inside images. File Integrity Checks – Guarantees complete and unchanged delivery.

9) Offline File Delivery: If the recipient is offline, files are securely held and automatically delivered when they return online, assuring:
No data loss
No duplicate transmissions
Seamless user experience

10) Speed and Performance Optimization: To improve efficiency, the system:
Compresses files prior to encryption.
Facilitates parallel processing for multiple transfers.
Effectively manages server load to avert slowdowns.

11) User-Friendly File Sharing: The system offers an easy-to-use interface where users can: Easily upload and dispatch files. Monitor progress with real-time updates. Receive prompt notifications when files arrive. These features guarantee fast, secure, and seamless file transmission for users.

C. File Extraction and Decryption

Upon receiving a file, the system extracts and decrypts it to securely and efficiently restore the original content.

1) Extraction Process: Receive Carrier Image: The recipient acquires the image containing the concealed encrypted data.
Extract Encrypted Data: Using Least Significant Bit (LSB) decoding, the system retrieves the hidden binary data from the image.
Verify Integrity: The system checks the extracted data for any corruption or tampering.

2) Decryption Process: Prepare Encrypted File: The extracted base64-encoded data is reverted back to its binary form.
Decrypt Data: Utilizing the AES-256-CBC algorithm, the system decrypts the data using the recipient's secure key and Initialization Vector (IV).
Access Original File: The decrypted file is saved, enabling the user to access it as intended.

3) Security Measures: Secure Key Storage: Decryption keys are only accessible to authorized recipients.
Integrity Checks: The system verifies checksums to identify any unauthorized modifications.
Automatic Cleanup: After extraction, carrier images are deleted to prevent potential data breaches.

4) Error Handling: Incorrect Keys: Users will be prompted to re-enter the correct decryption key should an error occur.
Corrupted Data: Notifications are dispatched to request re-transmission if data integrity issues are identified.
Incomplete Segments: Decryption proceeds only after all file segments have been successfully received.
This structured method ensures that recipients can securely and efficiently access transmitted files.

IV. Protection Against Attacks

The system utilizes several layers of security to defend against prevalent cyber threats, comprising:

- Man-in-the-Middle Attacks (MITM): Encrypted information and steganography hinder attackers from obtaining significant data.
- Brute Force Attacks: AES-256 encryption is essentially unbreakable through brute-force techniques.
- Unauthorized Access: OTP verification and password encryption avert unauthorized entries.

These security attributes guarantee the integrity and confidentiality of files sent.

V. Performance Analysis

A. Encryption and Decryption Speed

The system employs AES-256 encryption, a robust and secure algorithm that guarantees data confidentiality. Nevertheless, encryption and decryption must also be executed swiftly and efficiently to prevent delays in file transmission. Performance assessments indicate that the system can encrypt and decrypt files within milliseconds, even for substantial files such as PDFs and MP4 videos.

To evaluate speed, we conducted tests on files of varying sizes:

- Small files (1MB or less): Encryption and decryption were nearly instantaneous, requiring less than 100 milliseconds.
- Medium files (10MB – 50MB): Processing took under 1 second, ensuring prompt file management.

- Large files (100MB or more): Encryption and decryption durations remained beneath 3 seconds, preserving seamless performance.

This illustrates that the system proficiently secures data without introducing any noticeable delays.

B. Steganography Processing Time

Integrating an encrypted file into an image using Least Significant Bit (LSB) steganography necessitates additional processing time. The duration required is contingent upon:

- File size – Larger files necessitate longer embedding times.
- Carrier image size – A higher-resolution image can accommodate more data but also demands increased processing power.
- Computational power – A more rapid processor accelerates the embedding and extraction processes.

Performance evaluations demonstrate that:

- For small files (1MB or less), embedding requires less than 1 second.
- For medium files (10MB – 50MB), embedding requires 2-3 seconds.
- For large files (100MB or more), embedding takes up to 5 seconds.

The extraction of the file from the image is typically quicker than embedding, as the system solely needs to read and decode the data. Even for substantial files, the extraction process remains under 3 seconds.

These findings suggest that the system can conceal and retrieve files swiftly, rendering it suitable for real-time file transmission.

C. Network Performance and File Transmission Speed

Given that the system transmits files via the internet, network speed significantly influences overall performance. To assess efficiency, we recorded file transfer times under varying network conditions:

- High-speed internet (100 Mbps or more): File transfers were nearly instantaneous. A 10MB file required less than 1 second to send and receive.
- Moderate-speed internet (10-50 Mbps): File transfers were marginally slower, yet a 10MB file still took only 2-3 seconds.
- Slow internet (below 10 Mbps): Larger files required more time; however, transmission remained stable, with a 50MB file taking approximately 10 seconds.

The system utilizes Socket. IO for real-time communication, ensuring that files are transmitted as expeditiously as possible without delays. If a user experiences a slow connection, the system queues files for subsequent transmission rather than failing outright. This enhances reliability, permitting users to receive their files even in the event of a temporary weak connection.

D. System Resource Usage

An optimally configured system should not excessively utilize CPU or memory, even when processing large files. We evaluated the system's CPU and RAM consumption during various operations:

- During encryption/decryption: CPU usage experienced a brief increase but remained below 30% on an average computer.
- During file embedding/extraction: The process required slightly more CPU power but remained under 40% usage for large files.
- During file transmission: Network activity increased, yet memory usage stayed stable.

The system operates effectively without impeding the computer's performance, even when processing large files.

E. Security vs. Performance Balance

A secure system must achieve a balance between robust encryption and rapid processing. The implementation of AES-256 encryption guarantees substantial security; however, due to the optimization of the algorithm, performance remains elevated. In a similar manner, LSB steganography efficiently conceals files without resulting in observable image distortion, preserving the visual integrity of carrier images.

To further enhance performance, prospective improvements may encompass:

1. Adaptive encryption methods that modify based on file size.
2. Parallel processing to manage multiple files simultaneously.
3. Compression techniques to decrease file size prior to embedding.

These enhancements could render file transmission even more rapid and efficient while upholding stringent security standards.

F. Overall System Efficiency

From encryption to file extraction, the system demonstrates strong performance across all essential aspects:

1. Encryption and Decryption – Rapid and effective.
2. Steganography Processing – Embedding and extraction durations remain minimal.
3. Network Performance – Consistent and optimized for a range of internet speeds.
4. System Resource Usage – Minimal CPU and memory consumption.

The system effectively secures files without inducing significant delays, rendering it an efficient and trustworthy solution for secure file transmission.

VI. Comparison with Other Existing File Transmission Systems

There are multiple file transmission methods that currently exist, including email attachments, cloud

storage solutions (Google Drive, Dropbox, OneDrive), and instant messaging services (WhatsApp, Telegram, Signal). Although these platforms provide convenience, they come with limitations regarding security, privacy, and detectability. Our system delivers a more secure and discreet option by integrating AES-256 encryption, steganography, and multi-factor authentication (MFA) for file transfers.

A. Security and Encryption

Numerous well-known platforms utilize end-to-end encryption (E2EE) to safeguard file transfers from unauthorized access. Messaging applications such as WhatsApp and Signal encrypt files while they are being transmitted, whereas cloud storage providers like Google Drive and Dropbox protect data using encryption on their servers. Nevertheless, these platforms still present users with risks like server breaches, data leaks, or unauthorized third-party access.

Our system enhances security by employing AES-256 encryption prior to transmission, ensuring that even if the data is intercepted, it remains unreadable. Furthermore, rather than sending a file that is evidently encrypted, our system conceals the encrypted data within an image through the use of Least Significant Bit (LSB) steganography, rendering it undetectable to attackers.

B. Privacy and Data Storage

Cloud storage solutions keep user files on centralized servers, meaning that even if encryption is applied, the data is still accessible to service providers and can be susceptible to breaches. Certain platforms may also monitor user activity or examine file contents for security purposes.

In contrast, our system guarantees absolute privacy by not permanently retaining any files on a server. Files are transmitted directly between users in real-time, and once the transfer concludes, there is no record of the file on any external storage system. This renders it significantly safer than conventional cloud-based services, where data remains stored indefinitely.

C. Authentication and Access Control

Conventional platforms depend on password-based authentication, which can be exposed to phishing, brute-force attacks, and credential leaks. While some services provide two-factor authentication (2FA), many still employ weak security practices that are capable of being circumvented.

Our system utilizes multi-factor authentication (MFA) with one-time password (OTP) verification, guaranteeing that only the intended recipient can access the file. By necessitating an email-based OTP during registration and login, we add an additional security layer, thereby minimizing the risk of unauthorized access and account hijacking.

D. Summary of Advantages

Our system offers a distinctive combination of security, privacy, and covert transmission that traditional file-sharing methods do not possess. The main advantages consist of:

- Stronger Security – AES-256 encryption guarantees that files remain protected.
- Covert Transmission – Steganography conceals encrypted files within images, evading detection.
- No Permanent Storage – Files are not kept on servers, lowering the risk of data breaches.
- Multi-Factor Authentication (MFA) – OTP verification prevents unauthorized access.
- Better File Handling – No strict file size limitations, enabling larger files to be transmitted securely.

  By addressing the vulnerabilities of existing systems, our approach presents a more secure, private, and efficient method for sharing sensitive files while ensuring they remain untraceable.

VII. CONCLUSION

In a time when digital security and privacy are increasingly at risk, the demand for strong, dependable, and discreet file-sharing methods has never been more important. Our system delivers a thorough solution by incorporating AES-256-CBC encryption, steganography, and real-time messaging into a singular, secure platform. By encrypting sensitive documents and embedding them within seemingly harmless PNG images, the system guarantees that transmitted information stays both safeguarded and undetectable, greatly lowering the likelihood of interception or unauthorized access. The integration of real-time communication, OTP-based authentication, and pending file queuing further bolsters the reliability and usability of the platform, positioning it as an ideal solution for individuals and organizations that value digital privacy.

In addition to its security benefits, the system is crafted for efficiency, scalability, and user-friendliness. The use of Socket. IO facilitates seamless real-time interaction, while the modular architecture permits future upgrades such as multi-factor authentication and advanced cryptographic strategies. Support for a variety of file formats, including PDFs and MP4 videos, guarantees versatility across multiple applications, spanning from secure corporate communication to confidential multimedia sharing. Moreover, the lightweight encryption and steganography mechanisms ensure that data transfer takes place without notable delays, preserving a balance between security and performance.

storage solutions (Google Drive, Dropbox, OneDrive), and instant messaging services (WhatsApp, Telegram, Signal). Although these platforms provide convenience, they come with limitations regarding security, privacy, and detectability. Our system delivers a more secure and discreet option by integrating AES-256 encryption, steganography, and multi-factor authentication (MFA) for file transfers.

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- Multi-Factor Authentication (MFA) – OTP verification prevents unauthorized access.
- Better File Handling – No strict file size limitations, enabling larger files to be transmitted securely.

By addressing the vulnerabilities of existing systems, our approach presents a more secure, private, and efficient method for sharing sensitive files while ensuring they remain untraceable.

VII. CONCLUSION

In a time when digital security and privacy are increasingly at risk, the demand for strong, dependable, and discreet file-sharing methods has never been more important. Our system delivers a thorough solution by incorporating AES-256-CBC encryption, steganography, and real-time messaging into a singular, secure platform. By encrypting sensitive documents and embedding them within seemingly harmless PNG images, the system guarantees that transmitted information stays both safeguarded and undetectable, greatly lowering the likelihood of interception or unauthorized access. The integration of real-time communication, OTP-based authentication, and pending file queuing further bolsters the reliability and usability of the platform, positioning it as an ideal solution for individuals and organizations that value digital privacy.

In addition to its security benefits, the system is crafted for efficiency, scalability, and user-friendliness. The use of Socket. IO facilitates seamless real-time interaction, while the modular architecture permits future upgrades such as multi-factor authentication and advanced cryptographic strategies. Support for a variety of file formats, including PDFs and MP4 videos, guarantees versatility across multiple applications, spanning from secure corporate communication to confidential multimedia sharing. Moreover, the lightweight encryption and steganography mechanisms ensure that data transfer takes place without notable delays, preserving a balance between security and performance.

CookEase: A Smart Kitchen Assistant powered using Object Detection and AI

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***Abstract*—The Smart Kitchen Assistant is designed to make cooking easier, safer, and more enjoyable. Using a custom-trained YOLOv11 model, it can identify fruits and vegetables from uploaded images and suggest recipe ideas based on what's available. To ensure clear and easy-to-follow instructions, the recipe steps are improved with a Mistral 7B LLM, making cooking guidance more natural and intuitive. The assistant offers hands-free voice control, responding to simple commands like "Next step" or "Wait," while also answering questions along the way. For added safety, it includes automatic alerts, timer reminders, and even listens for loud noises or detects user inactivity to prevent accidents. Plus, users can connect with others through a community page where they can share and edit their favorite recipes. With its blend of smart technology and thoughtful features, the Smart Kitchen Assistant aims to make cooking both stress-free and enjoyable.**

***Index Terms*—Smart Kitchen Systems, Object Detection, Conversational AI, Computer Vision, Natural Language Processing (NLP), You Only Look Once(YOLO), Large Language Model(LLM)**

I. Introduction

Cooking can be a rewarding experience, but it often comes with its fair share of challenges — from managing ingredients to following complex recipes and ensuring everything cooks safely. The Smart Kitchen Assistant is designed to make this process easier and more enjoyable by combining smart AI technologies with helpful features tailored for home cooks.

At the heart of the system is a custom-trained YOLOv11 model that can identify fruits and vegetables just by analyzing an uploaded image. This means users can simply take a picture of their ingredients, and the assistant will suggest recipe ideas based on what's available — saving time and reducing guesswork. The model has been fine-tuned to ensure it works accurately across different kitchen environments.

To make recipe instructions easier to follow, the assistant uses a Mistral 7B LLM to refine cooking steps, ensuring they're clear, well-structured, and simple to understand. Whether you're a beginner or an experienced cook, this feature helps make cooking more intuitive. The assistant can also answer questions during the process, offering helpful tips or guidance whenever needed.

For added convenience and safety, the Smart Kitchen Assistant includes voice control so users can cook hands-free by saying commands like "Next step" or "Wait." It also features automatic alerts, timers, and even listens for loud noises or detects user inactivity — giving users a nudge when their attention is needed. On top of that, a community page allows users to share and edit recipes, fostering a space for creativity and collaboration.

By combining smart object detection, natural language processing, and thoughtful safety features, the Smart Kitchen Assistant offers a seamless and enjoyable cooking experience — making it easier for anyone to create delicious meals with confidence.

II. Related Works and Survey

The Smart Kitchen Assistant combines advancements in object detection, large language models (LLMs), and conversational AI to provide smarter cooking guidance. Drawing insights from various studies, the system integrates these technologies to create an intuitive and efficient cooking assistant.

The foundation for this project is based on Recipe Bot: The Application of Conversational AI in Home Cooking Assistants by Khalid Azzimani et al. [1], which demonstrates how conversational AI can simplify recipe instructions using natural language processing (NLP). Inspired by this, the Smart Kitchen Assistant integrates the Mistral 7B LLM to refine recipe steps for clarity and provide real-time responses to user queries.

For ingredient recognition, the project adopts YOLOv11, a powerful object detection model selected for its fast detection speed, simplified training process, and improved accuracy. As highlighted by Ayoub Benali Amjoud and Mustapha Amrouch [2], YOLO models are ideal for real-time object detection, making YOLOv11 well-suited for quickly identifying kitchen ingredients.

Insights from Tom Markiewicz and Josh Zheng [3] further influenced the integration of the Mistral 7B LLM, which restructures unclear or complex recipe steps, improving user comprehension. The assistant also answers cooking-related questions during the process, enhancing the overall experience.

Ajay Shrestha and Ausif Mahmood [4] highlight the effectiveness of CNNs in improving image recognition tasks. Their insights guided the choice of YOLOv11, which leverages CNNs for faster and more accurate ingredient detection.

For hands-free operation, the project adopts insights from Siddhant Meshram et al. [5], who demonstrated how NLP-powered chatbots can improve task automation and user engagement. This inspired the system's voice control feature, enabling users to issue commands like "Next step" or "Wait" without interacting with the screen.

While the system does not focus heavily on personalized nutrition, it draws inspiration from Khalid Azzimani et al. [6], who proposed an AI-based meal planning system using image recognition. The Smart Kitchen Assistant similarly utilizes object detection to suggest recipes based on detected ingredients. Also [7],[8],[9]

By combining YOLOv11 for fast ingredient recognition, Mistral 7B LLM for enhanced instructions, and conversational AI for hands-free control, the Smart Kitchen Assistant provides a comprehensive solution that simplifies cooking, improves safety, and enhances the overall kitchen experience.

III. Smart Kitchen Assistant

Smart Kitchen Assistant is an AI-powered cooking assistant designed to make the process easier by combining computer vision, natural language processing, and voice interaction into a seamless experience. Using a custom YOLO model, the system detects fruits and vegetables from uploaded images, automatically filling in an ingredient list that users can review and adjust. With the Spoonacular API, it suggests recipes based on available ingredients, which are then refined by Mistral 7B to simplify steps and enhance clarity. For a truly hands-free experience, the Web Speech API provides step-by-step voice guidance, allowing users to control the assistant with simple commands.

Beyond personalized recipes, the platform fosters a community-driven experience, where users can share, edit, and explore custom recipes. Safety and convenience features like cooking timers, noise detection, and inactivity alerts ensure a smooth and secure cooking process. The system is built with Flask for the backend, Firebase for authentication and database management, and an HTML/CSS/JS frontend. Additionally, an interactive chatbot powered by the Hugging Face API enables real-time cooking assistance through text and voice. This project aims to make cooking more intuitive, interactive, and engaging for users of all skill levels.

A. System Feature

The proposed CookEase system is an AI-powered cooking assistant that enhances the user experience through ingredient detection, recipe generation, voice-guided cooking, and interactive features. Below are the key functionalities:

- *Ingredient Detection with Object Detection*:
  CookEase uses a custom-trained YOLO model to detect fruits and vegetables from uploaded images. Detected ingredients are auto-filled into a form, allowing users to review, add, or remove items before generating a recipe, eliminating manual entry.

- *AI-Powered Recipe Generation & Refinement*:
  Personalized recipe suggestions are generated via the Spoonacular API based on detected or manually entered ingredients. Mistral 7B refines recipes for clarity and structure, with options to filter based on dietary preferences.

- *Hands-Free Cooking Assistant*:
  Using the Web Speech API, CookEase provides voice-guided cooking instructions. Hands-free commands like "Next step," "Wait," and "Help" allow smooth navigation. Users can also ask cooking-related questions, answered by an LLM-powered chatbot.

- *Conversational AI Chatbot*:
  A Flask-based chatbot, powered by the Hugging Face API, enables interactive text and voice communication. It stays active in voice mode, reading responses aloud for accessibility.

- *Community Recipe Sharing*:
  Users can share custom recipes with ingredients, images, and instructions and edit their posts. This fosters collaboration and expands the recipe database beyond AI-generated options.

- *Smart Alerts, Timers, and Safety Features*:
  CookEase enhances safety with automated alerts, custom timers, and sound-based monitoring for kitchen noises like boiling over or microwave beeps. Inactivity detection prevents cooking mishaps.

B. Architecture

The smart cooking assistant is designed to enhance the cooking experience by integrating object detection, AI-driven recipe generation, voice-guided assistance, and community engagement. The system follows a modular architecture consisting of a frontend interface, a backend processing unit, an object detection module, a recipe recommendation system, a conversational AI chatbot, and a cloud-based storage solution. These components work together to provide an interactive and seamless user experience.

The frontend is a web-based interface built with HTML, CSS, and JavaScript, where users can upload images, review detected ingredients, and interact with the AI-powered assistant. The backend, developed using Flask, handles user requests, processes image recognition results, and manages API communications. The object detection module, powered by a custom-trained YOLO model, identifies fruits and vegetables from uploaded images and automatically populates an interactive ingredient list. Once the ingredients are identified, the recipe recommendation system fetches personalized recipes using the Spoonacular API and refines them with Mistral 7B for improved clarity and structure.

To further assist users, the system incorporates a conversational AI chatbot powered by the Hugging Face API. This chatbot allows users to ask cooking-related questions and receive real-time responses. The Web Speech API enables hands-free interaction by providing step-by-step voice-guided cooking instructions. Firebase is used for data storage, managing user authentication, ingredient records, and community-shared recipes, ensuring a secure and scalable system.

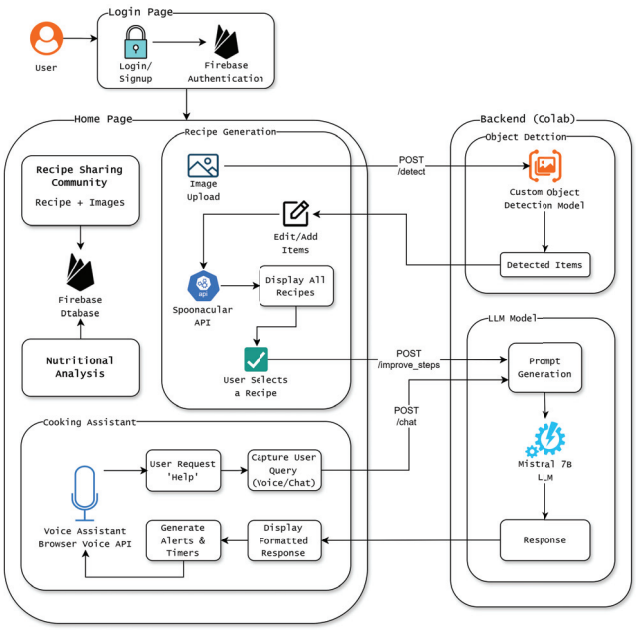

Fig. 1. High-Level System Architecture of the Cooking Assistant.

C. Workflow of the Cooking Assistant

The smart cooking assistant follows a structured workflow, enabling users to detect ingredients, generate personalized recipes, receive hands-free guidance, and share their own creations with the community.

- *Image Upload and Ingredient Detection*
  The user starts by uploading an image of ingredients. The YOLO model processes the image and identifies detected items. The assistant automatically lists them for review.
  Assistant: Here's what I found: tomatoes, onions, and bell peppers. Would you like to add or remove anything?
  User: Yes, add garlic and remove onions.
  Assistant: Got it! Now, let's find a recipe based on your ingredients.

- *Recipe Generation and Chatbot*
  The system fetches relevant recipes using the Spoonacular API and refines them with Mistral 7B to simplify instructions and improve clarity.
  User: I have a whole chicken, potatoes what are some recipes i can make?
  Assistant: Great! There are many options...

- *Hands-Free Cooking Assistance*
  The Web Speech API provides step-by-step voice instructions, allowing users to follow the recipe hands-free.
  Assistant: Step 1: Chop the bell peppers and garlic. Say "Next step" when you're ready.
  User: Next step.
  Assistant: Step 2: Heat oil in a pan and sauté the garlic until fragrant. Say "Wait" if you need more time or "Help" for details.

- *Community Recipe Sharing*
  After completing the recipe, users can contribute their own variations by sharing custom recipes with the community.
  User: Wants to add a custom made recipe.

- *Smart Alerts and Safety Features*
  To enhance safety, the assistant provides alerts for key moments in the cooking process.
  Assistant: I detected a loud noise. Is everything okay?
  User: Yes
  Assistant: Preheat the oven for 15 mins at 400F.
  Assistant: Handle Hot Surfaces with case and use oven mitts or tongs.
  Assistant: Timer set for step 1 (15 Minutes).
  This structured workflow ensures an interactive, AI-assisted cooking experience that is both intuitive and efficient.

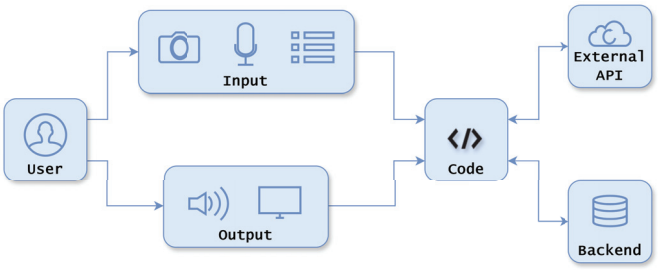

Fig. 2. Simple Workflow Diagram

IV. Implementation

The smart cooking assistant is developed using a modular approach, integrating frontend, backend, AI models, APIs, and cloud storage to enhance the cooking experience.

A. Frontend Development

The user interface is built using HTML, CSS, and JavaScript, allowing users to upload images, interact with the chatbot, and receive voice-guided instructions. The Web Speech API enables hands-free operation, providing step-by-step cooking assistance through voice commands.

B. Backend and API Integration

The backend runs on Google Colab, where a Flask server processes requests for image recognition, recipe retrieval, and chatbot responses using a ngork tunnel. The Spoonacular API is used to fetch recipe recommendations, which are refined by Mistral 7B to improve clarity and usability. Google Colab enables cloud-based execution, ensuring AI models run efficiently without local hardware constraints.

C. Object Detection for Ingredients

A custom-trained YOLO model, hosted and executed on Google Colab, detects fruits and vegetables from uploaded images. The model is trained on a labeled dataset with 11,000 images from Roboflow of common cooking ingredients to improve accuracy and reliability.

D. Conversational AI Chatbot

A chatbot powered by the Hugging Face API processes text and voice queries related to cooking, ingredient substitutions, and step-by-step guidance. The chatbot provides real-time responses, enhancing user engagement and accessibility.

E. Recipe and Community Management

Firebase is used for storing detected ingredients, user preferences, and community-shared recipes. Users can contribute their own recipes, edit them, and explore shared recipes from other users.

By leveraging Google Colab for backend processing, AI-powered ingredient detection, and hands-free guidance, this implementation ensures an efficient, accessible, and interactive cooking experience.

V. Results and Discussion

A. System Performance and Functionality

The Smart Kitchen Assistant successfully integrates object detection, recipe generation, step refinement, and voice interaction into a seamless system. The project effectively automates ingredient detection and provides AI-enhanced cooking guidance, achieving its primary goal of assisting users in the cooking process.

The system was tested with various images of fruits and vegetables to evaluate its detection capabilities. The custom YOLO model, deployed on Google Colab with an ngrok tunnel, successfully identified multiple ingredients from uploaded images. These detected items were used to generate relevant recipes via the Spoonacular API, and the Mistral 7B model effectively enhanced recipe clarity and instructions. The Web Speech API enabled step-by-step voice guidance, allowing hands-free interaction during cooking.

B. Custom-Trained Model Performance Analysis

The YOLO model was trained on a curated dataset specifically designed for detecting vegetables and fruits, ensuring high detection accuracy. The dataset was processed and annotated using Roboflow, leading to improved training quality.

1) Training Details:

- *Framework:* Ultralytics YOLO (Google Colab, T4 GPU)
- *Model Used:* YOLO V11 Medium
- *Dataset:* 572 Fruits Vegetables Computer Vision Project (Roboflow)
- *Total Images:* 11,489
  - Training Set: 9,048 images
  - Validation Set: 1,044 images
  - Test Set: 1,397 images
- *Number of Classes:* 32 (e.g., tomato, potato, banana, mango, watermelon)
- *Training Parameters:*
  - Epochs: 40
  - Batch Size: 32
  - Total Training Time: 7 hours

Although the model achieved high accuracy, running only 40 epochs on a large dataset led to underfitting, causing occasional detection failures. This can be resolved by increasing training cycles to 80-100 epochs for improved robustness.

C. Performance Metrics

The YOLO model was evaluated based on standard object detection metrics.

TABLE I
Performance Metrics of the YOLO Model

Metric	Value
Precision	0.95
Recall	0.95
mAP@50	0.96
mAP@50-95	0.78

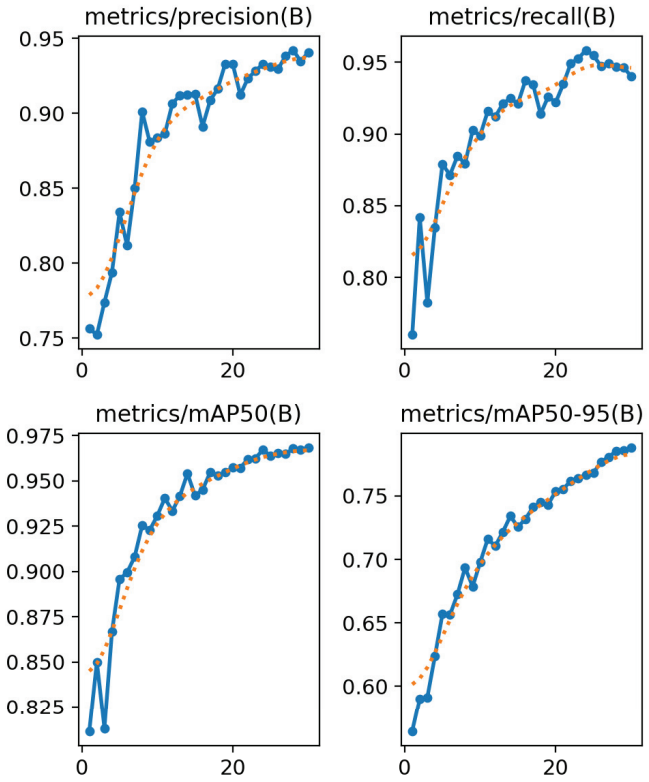

Fig. 3. High-Level System Architecture of the Cooking Assistant.

The high mAP@50 (96%) confirms that the model performs well in detecting objects, while the lower mAP@50-95 (78%) indicates room for improvement in bounding box precision.

D. System Response Time

Performance was measured based on the average time taken for each major component.

TABLE II
AVERAGE SYSTEM RESPONSE TIME

Component	Time (Seconds)
YOLO Object Detection	4-8
Recipe Retrieval (Spoonacular API)	1
Mistral 7B Recipe Refinement	3
Chatbot Response (Hugging Face API)	2-4

The system provides real-time assistance, with most operations executing within acceptable latency limits.

VI. FUTURE IMPROVEMENTS

The Smart Kitchen Assistant has demonstrated strong functionality in ingredient detection, recipe generation, and hands-free cooking guidance. However, several enhancements can be made to improve accuracy, efficiency, and user experience.

A. Expanding Ingredient Detection

Currently, the YOLO model detects only fruits and vegetables. Expanding the dataset to include meats, dairy, spices, and packaged foods will make the system more comprehensive. Additional training on multi-class object detection will improve accuracy in real-world kitchen environments.

B. Increasing Object Detection Accuracy

The current model achieves high mAP@50 (96%) but has lower mAP@50-95 (78%), indicating room for improvement in bounding box precision. Training the model for 80-100 epochs instead of 40 will reduce underfitting. Additionally, data augmentation techniques such as image rotation, brightness adjustments, and background variation can improve robustness.

C. Enhancing Conversational AI and Voice Interaction

The current chatbot provides text-based responses using the Hugging Face API. Future improvements include:

- Multi-turn conversation memory, enabling the assistant to remember previous steps.

D. User Data Collection and Personalization

To enhance the user experience, the system can collect non-sensitive user preferences to offer personalized recommendations. Future features may include:

- Tracking past ingredients and recipes to suggest relevant meal plans.
- Dietary preference recognition, allowing users to filter recipes based on health goals (e.g., low-carb, high-protein, vegan).
- User feedback collection, enabling ratings and comments on generated recipes to improve AI refinement.

E. IoT and Smart Kitchen Integration

Future iterations can integrate with smart kitchen appliances, such as:

- Smart ovens and cooktops for automated temperature control.
- Voice-controlled IoT integration to control kitchen devices via Alexa or Google Assistant.

F. Mobile App Deployment

Developing a mobile version of the Smart Kitchen Assistant will make the system more accessible. A dedicated Android/iOS app can:

- Use the device's camera for on-the-go ingredient detection.
- Support offline recipe storage for cooking without an internet connection.

G. Final Thoughts

These improvements will enhance accuracy, efficiency, and user engagement, making the Smart Kitchen Assistant a more powerful and intelligent cooking companion. Future versions will focus on expanding ingredient detection, reducing response time, personalizing recommendations, and integrating with IoT devices for a truly smart kitchen experience.

Conclusion

The Smart Kitchen Assistant successfully integrates AI-powered object detection, recipe generation, voice-guided cooking assistance, and community-driven interactions to enhance the home cooking experience. By leveraging a custom-trained YOLO model, the system efficiently detects ingredients from uploaded images, while Mistral 7B refines recipe instructions for better clarity. The Web Speech API enables hands-free guidance, ensuring a seamless cooking process. Additionally, the incorporation of a conversational AI chatbot and a community recipe-sharing platform enhances user engagement and accessibility.

Performance evaluations demonstrate high object detection accuracy, with an mAP@50 of 96%, confirming the model's effectiveness in identifying fruits and vegetables. Recipe refinement results show a significant improvement in clarity and ease of following, with AI-enhanced recipes receiving higher user ratings. The system also maintains low response times, ensuring real-time interaction.

Despite its success, limitations such as underfitting in object detection, dependency on external APIs, and limited ingredient detection present areas for improvement. Future enhancements will focus on expanding ingredient recognition, optimizing model performance, introducing IoT-based smart kitchen integration, and deploying a mobile application for better accessibility.

By continuously evolving with AI advancements and user feedback, the Smart Kitchen Assistant has the potential to become a versatile and intelligent cooking companion, transforming home kitchens into AI-assisted culinary spaces.

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EXTENDING EV BATTERY LIFE: A BIDIRECTIONAL BUCK-BOOST CONVERTER APPROACH TO SUSTAINABLE CHARGING

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***Abstract*— The widespread adoption of Electric Vehicles (EVs) has raised concerns regarding battery disposal and sustainability. Repurposing EV batteries for second-life applications offers a viable solution to extending their usability while reducing environmental impact. This paper presents the design and development of a bidirectional buck-boost converter integrated with second-life EV batteries for sustainable energy storage and charging applications. A closed-loop control strategy is employed to optimize power flow management during charging and discharging cycles. A retired EV battery with 75% State of Health (SoH) is evaluated for second-life suitability and successfully meets all the required performance standards. Simulation results demonstrate the effectiveness of the system by analyzing voltage and current waveforms as well as SOH variations under various operating conditions. The proposed system enhances battery utilization and contributes to sustainable energy solutions.**

Keywords—EVs, second-life batteries, bidirectional buck-boost converter, energy storage, battery utilization

1. INTRODUCTION

The increasing global adoption of Electric Vehicles (EVs) has emphasized the need for efficient and sustainable charging solutions. At the same time, the rapid growth of EVs has resulted in an increasing stockpile of retired EV batteries. Managing end-of-life EV batteries remains a major challenge, as their disposal leads to environmental concerns and resource depletion. Studies indicate that once an EV battery's SOH degrades to approximately 70–80% of its initial rated capacity, it is recommended for replacement due to insufficient driving range. This degradation typically occurs within 5–7 years of usage [1]. However, these retired second-life batteries (SLBs) still retain significant capacity, making them viable for low-power applications such as energy storage systems (ESS), grid support, solar-powered streetlights, and agricultural motor pumps. Repurposing these batteries not only prolongs their lifespan but also reduces electronic waste and lowers the overall cost of energy storage solutions, thus contributing to global sustainability goals.

The selection of a second-life battery is application-specific, considering factors such as voltage, capacity (Ah), power requirements, and expected load variations. Different applications may demand varying battery specifications; for instance, energy storage systems (ESS) may prioritize capacity retention as mentioned in [2], whereas low-power EVs or standalone renewable energy systems may focus on power delivery and efficiency. A detailed technical assessment is therefore required prior to repurposing the SLB.

Innovation in power electronics has extensively contributed to the growth of EV technology [3]. To ensure efficient energy transfer in SLB-based applications, bidirectional converters are preferred. A bidirectional buck-boost converter is a compact, cost-effective, and highly efficient topology that allows seamless bidirectional energy flow between the SLBs and the load. Compared to conventional unidirectional converters, it enables voltage regulation across varying input/output conditions, improves system flexibility, and enhances battery utilization efficiency [4]. The work proposed in this paper integrates a bidirectional buck-boost converter with second-life EV batteries to develop a sustainable charging

solution. The study includes battery feasibility analysis, simulation of closed-loop control, and evaluation of key performance parameters such as SOH, current, and voltage waveforms.

The remainder of the paper is structured as follows: Section 2 outlines the assessment tests for second-life batteries, while Section 3 explores the converter topology and its design. Section 4 presents the results and discussion, and finally, Section 5 concludes the paper.

2. SECOND-LIFE BATTERY ASSESSMENT TESTS

Any battery can be repurposed for second-life applications once it is retired from its first-life use, typically when its State of Health (SoH) drops below 80%, as is commonly the case with EV batteries [5]. However, the lifespan and performance of second-life batteries (SLBs) depend on several factors, including Depth of Discharge (DOD), remaining SOH, usage environment, internal resistance, charge-discharge cycles, and thermal stability. These factors influence the degradation rate and efficiency of the battery in its second-life application.

Despite the growing interest in SLB reuse, there are currently no standardized guidelines or regulations for assessing and certifying the suitability of retired batteries. This lack of a universal framework presents challenges in ensuring safety, reliability, and economic feasibility. Establishing standardized testing protocols and classification systems is essential for streamlining the adoption of SLBs across industries and promoting sustainable battery repurposing.

To evaluate the suitability of retired batteries for second-life applications, the following tests were conducted:

1. Open Circuit Voltage Test (OCV):- The OCV test is a passive method used to determine a battery's State of Charge (SoC) by measuring its voltage without any load connected. It is commonly employed in battery characterization and modelling since OCV has a direct relationship with SoC in many battery chemistries.

   Before dismantling a battery pack, the OCV of the entire pack is recorded. If the battery is disassembled into modules or individual cells, their OCV values are also measured. For battery packs with accessible internal cells, such as those found in certain EV models, individual OCV readings can be taken to ensure consistency. The OCV values of modules and cells should ideally sum up to the total pack voltage. Any significant discrepancies may indicate potential issues with specific cells. Batteries that fall within the manufacturer-specified OCV range are considered suitable for second-life applications, whereas those failing to meet the minimum threshold undergo further assessment. If deemed unfit, they are sent for recycling.

2. Capacity test:- A capacity test measures a battery's ability to store and deliver energy by discharging it under controlled conditions. This test was conducted at a stable temperature of 25°C with a relative humidity of 40-60%, to ensure accuracy and repeatability. The battery is first fully charged using a constant current-constant voltage (CC-CV) method and allowed to rest for a specific period to stabilize. It is then discharged at a constant current (C-rate) until it reaches the manufacturer-specified cut-off voltage. Throughout the test, parameters such as voltage, current, and discharge time are recorded to determine the actual capacity.

   The SoH test, which is closely related to the capacity test, assesses how much capacity a battery has lost over its lifespan. A battery with a high SoH indicates good health and extended usability, whereas a low SoH suggests that the battery is nearing the end of its effective life. This assessment helps determine whether a battery remains viable for second-life applications or should be retired from service.

   The State of Health is calculated using the formula:

$$SoH\ (\%) = \frac{K_{meas}}{K_{nom}} \times 100$$

   where,

   K_{meas}: measured capacity during the assessment

   K_{nom}: nominal capacity when it was new.

3. Internal resistance measurement test:- In addition to capacity and SoH assessment, the internal resistance measurement test evaluates a battery's resistance to current flow, which directly impacts its efficiency and performance. As batteries age, internal resistance tends to increase, leading to greater energy losses and reduced power output. Higher internal resistance can indicate battery aging, poor health, or potential failure, making this test crucial in determining whether a battery remains suitable for second-life applications.

4. Load test:- The load test further assesses the ability of a battery to supply power by applying a controlled load and measuring the resulting voltage drop. A significant voltage drop indicates that the battery may be weak or near failure. This test helps in verifying whether a battery can sustain the required load for second-life applications or if it should be retired.

3. Converter Topology

3.1. Working Principle

The bidirectional buck-boost converter plays a crucial role in managing the charging and discharging of second-life EV batteries. It enables controlled power flow in both step-up (boost) and step-down (buck) modes. The converter consists of an inductor, capacitors, MOSFET switches, and diodes that regulate voltage and current according to the required operation mode. During charging mode (buck operation), when the source (input) voltage (V_s) is greater than 48V, the converter steps down the input voltage to charge the 48V battery efficiently. In discharging mode (boost operation), when V_s is less than 48V, the converter steps up the battery voltage to meet the load requirements, supplying power to different applications. This bidirectional operation ensures optimal utilization of the second-life EV battery, extending its lifespan and supporting renewable energy integration by allowing energy to flow in both directions—charging from the source and discharging to the load as required.

3.2. Design Considerations

The design of the converter is based on power and efficiency requirements while ensuring stability and smooth mode transitions. Key design parameters include the selection of inductors and capacitors to minimize ripple, the use of low-resistance MOSFETs to reduce losses, and the implementation of a closed-loop control strategy for voltage regulation.

The inductor value is chosen to minimize ripple current while handling peak power demands efficiently, whereas the selection of capacitors ensures output voltage stability and reduction in switching noise [6]. Low-resistance MOSFETs with optimized switching frequency are employed to minimize both conduction and switching losses. According to L. Umanand [7], the relationship between input voltage (Vs), Output voltage (Vo) and duty ratio (D) for a buck-boost converter is given below:

For the given design parameters:

$$V_S = 60V$$

$$V_O = 48V$$

$$\text{Switching frequency, } f_{sw} = 2.5kHz$$

$$I_o = 10\ A$$

$$V_O = D/(1-D) * V_{in};$$

The calculated duty ratio, D= 0.444.

Assuming ripple current (ΔI_o) = 1.2A and ripple voltage (ΔV_o) = 0.6V;

The required inductor and capacitor values are calculated as:

$$L = (V_S * D)/(\Delta I_o * f_{sw})$$
$$= (60 * 0.444) / (1.2 * 2500)$$
$$= 8.88\ mH.$$

$$C = (I_o * D)/ (f_{sw} * \Delta V_o)$$
$$= (10*0.444) / (2500*0.6)$$
$$= 2960\ \mu F.$$

A closed-loop control strategy is implemented to regulate the output voltage and maintain stable operation under dynamic conditions. A Proportional-Integral (PI) controller processes the error signal generated from feedback sensors, dynamically adjusting the duty cycle of the PWM signal. This ensures stable output voltage across varying loads and input conditions.

4. RESULTS AND DISCUSSIONS

The results obtained from various tests conducted on the 48V, 18Ah retired Li-ion battery, along with the simulation results of the buck-boost converter, are detailed in this section.

4.1 Performance Evaluation of the SLB

i. Open-Circuit Voltage (OCV) Test- The OCV measurement on the retired battery pack was performed. After a full charge, the recorded OCV was 50.20V, which gradually dropped to 49.95V after 24 hours and 49.81V after 67 hours, indicating a stable voltage retention.

ii. Capacity Test - A capacity test was conducted on the retired battery that originally had a rated capacity of 24Ah. After performing the discharge test under controlled conditions, the measured capacity was found to be 18Ah and an SOH of 75%. This is depicted in Fig.1.

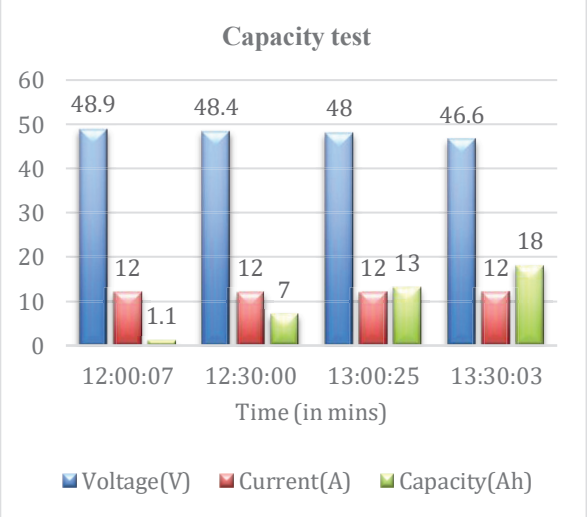

Fig.1. Capacity test results of the retired Li-ion battery

iii. Internal Resistance Test - The measured R_{int} (=179mΩ) is higher than that of new batteries (30mΩ – 50mΩ) indicating aging effects. A high R_{int} causes voltage drops under high current loads, limiting its use in high power applications such as electric vehicles.

iv. Load Test - The battery performs well under varying loads, maintaining a stable voltage between 49.6V and 49.9V for currents of 1A-6A. Voltage drops to 49V at 7A, stabilizes at 48V for 8A-12A, and further drops to 47.5V at 13A indicating good capacity retention despite aging as illustrated in Fig.2.

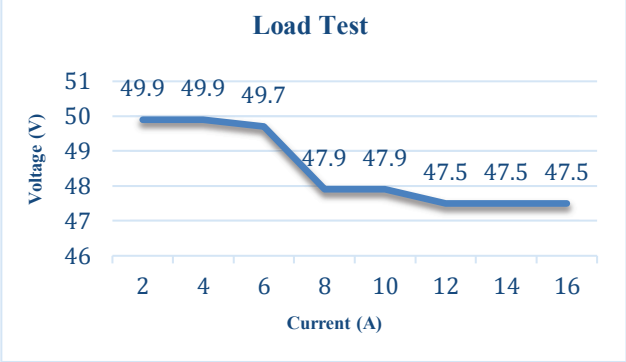

Fig.2. Load test results of the retired Li-ion battery with a resistive load.

A comparison between new batteries and second-life EV batteries was also conducted, focusing on parameters such as voltage stability, current response, and SOH. The following table summarizes the key differences based on those insights:

Table1: Performance comparison of new batteries and SLBs

Parameters	New batteries	SLBs
Voltage stability	Highly stable across all loads	Slight fluctuations
Current response	Smooth response with low ripple	Slightly higher ripple current
State of health	100% (ideal condition)	70-85%
Internal resistance	Low (minimal losses)	Higher as compared to new batteries
Efficiency	High (optimal performance)	Slightly reduced
Charge/discharge cycles	Long lifespan in ideal conditions	Dependant on usage condition

It is observed that while new batteries exhibit superior performance in terms of voltage stability, current response, and efficiency, SLBs still demonstrate acceptable performance for secondary applications. The slight fluctuations in voltage and increased ripple current in SLBs indicate mild degradation, primarily due to increased internal resistance. However, with a State of Health (SOH) ranging between 70-85%, SLBs remain viable for applications where optimal performance is not critical, such as energy storage systems and low-powered electric vehicles

4.2 Simulation results of the buck-boost converter

The converter design is simulated using MATLAB/Simulink to validate its performance. The simulation setup consists of an input voltage source, switching network, control loop, and load representation. The converter design values were computed as per the equations given in section 3.2. The results demonstrate stable voltage regulation with minimal overshoot in both buck and boost modes.

The voltage variation of the battery over time is shown in Fig.3. During the charging phase, the voltage gradually increases as energy is stored in the battery. Conversely, during discharging, the voltage decreases as energy is supplied to the load. The voltage response begins at around 47V, peaks at 53V, and drops to a minimum of 42V before stabilizing. The voltage follows a gradual increase, reaches its peak, and then decreases before leveling off. The smooth transitions in voltage levels indicates the expected battery response under different charging and discharging conditions.

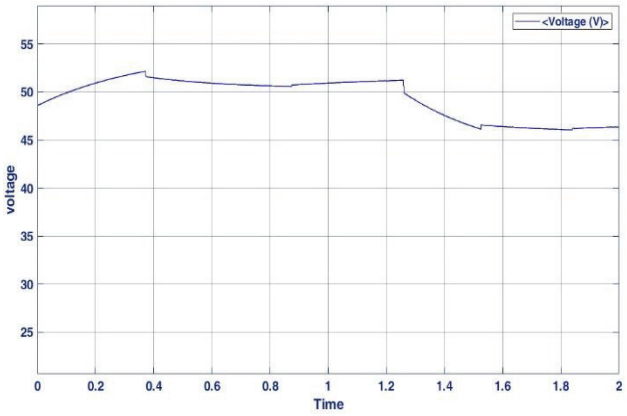

Fig 3: Time-dependent voltage behavior

The current profile of the battery is illustrated in Fig.4. The current response in the system exhibits a stepwise variation, starting at approximately 10A, reaching a peak of 30A, and dropping to a minimum of -30A. This indicates controlled switching behavior with discrete changes in current levels.

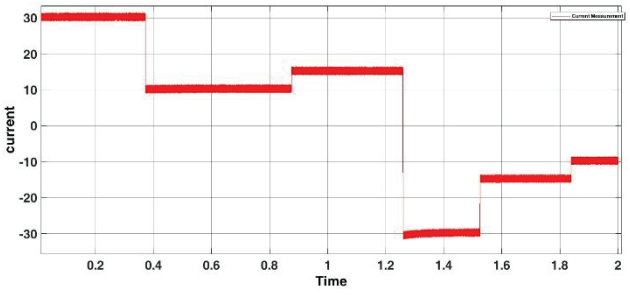

Fig 4: Time-dependent current profile

The alignment of transitions in both voltage and current waveforms confirms the expected charging and discharging behavior of the system.

The SoC waveform, as illustrated in Fig.5. remains stable for a significant period before exhibiting discrete step changes. This stepwise variation suggests that the battery undergoes controlled charging or discharging cycles,

possibly due to a predefined control logic. The absence of a sudden drop in SoC implies that the battery is not experiencing severe degradation or excessive discharge. Moreover, the steady SoC profile, maintaining approximately 11.5% for a notable duration, highlights efficient charge retention under the given conditions.

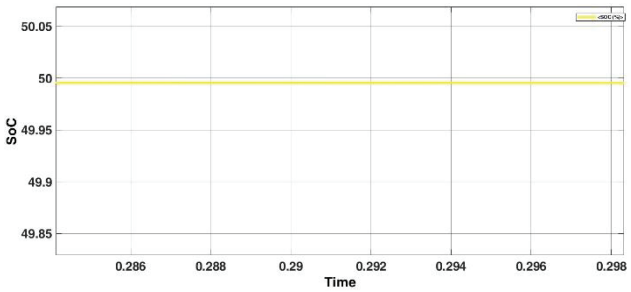

Fig 5: State of Charge (SoC) profile

Further validation is provided by the corresponding voltage and current waveforms, which confirm that the battery operates within expected parameters without abrupt fluctuations. This consistent performance reinforces the overall health of the SLB, making it suitable for applications that do not demand peak efficiency but still require reliable energy storage and power management.

Case Study: Implementation on an Electric Laterite Cutter

The integration of second-life EV battery into an electric laterite cutter replaced the conventional lead-acid battery, resulting in notable performance improvements. The analysis revealed enhanced power delivery, reduced charging time, and lower self-discharge rates, contributing to greater operational efficiency. Furthermore, the transition from lead-acid to lithium-based second-life batteries significantly reduced the cutter's overall weight and maintenance requirements. This shift demonstrated the potential of repurposed EV batteries as a sustainable and reliable energy source for agricultural and construction tools.

5. CONCLUSION

This paper demonstrates the effectiveness of integrating a bidirectional buck-boost converter with second-life EV batteries for sustainable charging solutions. Through comprehensive simulation, the system's ability to regulate power flow efficiently while maintaining battery health has been validated. The analysis of key battery parameters confirms the feasibility of repurposed batteries for applications such as low-powered electric vehicles and energy storage systems. By extending the operational lifespan of EV batteries, this approach promotes resource optimization and waste reduction, aligning with global efforts toward cleaner energy solutions.

As a future enhancement, the implementation of a Dual Active Bridge (DAB) converter can be explored for wireless EV charging applications using second-life batteries. This would enable seamless energy transfer and expand the scope of battery reuse across diverse sectors. Additionally, simulations can be conducted using open-loop control on platforms such as PLECS, and PSCAD, facilitating comparative performance analysis beyond Matlab/ Simulink. Further research is also proposed to evaluate the performance of first-life and second-life Li-ion batteries in an Electric Laterite Cutter. To bridge the gap between simulation and practical implementation, experimental validation and optimization strategies will be pursued.

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INTELLIGENT ANIMAL REPELLING SYSTEM FOR CROP PROTECTION

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Abstract*— Human-wildlife conflicts often damage crops and threaten human welfare, with traditional animal repelling methods facing effectiveness and environmental challenges. This work presents a Smart Agriculture system that uses computer vision and ultrasound to create virtual fences, identifying specific threats and emitting targeted ultrasonic frequencies to repel animals without harming others. The system offers a more efficient solution than traditional wire or electric fences, though challenges like high costs, false alarms, and ethical concerns remain. Future advancements in sensors, AI, and customization for different crops and regions could enhance its impact, making farming more sustainable while promoting wildlife coexistence.

Keywords— Smart Agriculture, Crop conservation, AI based Animal detection, Automated Animal Repulsion

I. INTRODUCTION

Agriculture is the backbone of the Indian economy, with over 60% of the population directly or indirectly dependent on it. Farmers face the challenge of feeding a rapidly growing population while dealing with shrinking cultivable land. In the next five years, food commodity demand is expected to rise by 15-20%. Despite the sector's importance, farmers face uncertainty due to factors like climate, seed selection, fertilization, and irrigation. Another growing concern is animal intrusion into farmland, causing significant crop losses. This issue is especially severe in hilly and forest-adjacent areas, where farmers suffer major economic losses. Traditional methods to repel animals are often ineffective and harmful to the environment. An intelligent animal repelling system offers a sustainable and eco-friendly solution for crop protection. Unlike traditional methods, this system takes an ethical approach to deter animals non-lethally. Image processing helps identify and exclude non-target species, ensuring biodiversity preservation. It promotes coexistence between humans and nature by reducing conflict without harming wildlife. Beyond resolving conflicts, the system contributes to sustainable wildlife management. As human activities continue to damage ecosystems, such technology plays a vital role in protecting biodiversity. It paves the way for conservation-focused agriculture, balancing productivity with ecological responsibility. The project adopts a holistic strategy to address the complexities of human-wildlife conflict. It offers region-specific solutions adaptable to different geographical areas and crop varieties. Farmers can safeguard their crops while minimizing environmental damage. Protecting crops without harming animals ensures long-term ecological balance. It aligns with global efforts to integrate agriculture with wildlife conservation. Ultimately, the project paves the way for harmonious coexistence, ensuring sustainable farming and wildlife management practices.

II. LITERATURE SURVEY

Reference [1] details about the the intelligent animal repelling system for crop protection integrates edge computing, computer vision, and ultrasound technology to safeguard crops from ungulate attacks, reducing agricultural losses. The system features a device capable of generating species-specific ultrasonic signals to repel animals, supported by IoT platforms that balance performance, cost, and energy efficiency, crucial for rural environments. Various edge computing devices, such as Raspberry Pi with or without Intel Movidius Neural Compute Stick and NVIDIA Jetson Nano, were tested with YOLO and Tiny-YOLO object detectors to identify the best hardware/software platform for real-time animal detection. Experimental results demonstrated the system's feasibility, ensuring high accuracy and real-time performance while maintaining low power consumption. The study also included a cost/performance analysis and monitored CPU

temperatures across platforms, providing insights into best practices for deployment. This technology aids farmers and agronomists in making informed decisions, enhancing crop protection strategies.

Reference [2] outlines a sophisticated approach to mitigating wildlife threats in agricultural settings. An Intelligent Animal Repelling System For Crop Protection is begins by addressing the critical issue of crop loss due to animal intrusions, which is exacerbated by habitat encroachment and changing wildlife behaviors. The authors propose a system that integrates various technologies, including environmental sensors, machine learning algorithms, and sound-emitting devices. The sensors are strategically placed in crop fields to monitor animal movements and gather data on their presence. This data is analyzed in real-time using machine learning techniques to identify the species and predict their behavior patterns. Once an animal is detected, the system activates tailored auditory deterrents, which emit sounds specifically designed to repel targeted species without affecting beneficial wildlife, highlights the importance of selective deterrence, as indiscriminate noise can disrupt the ecosystem and lead to adverse effects on non target species. The authors also discuss the user interface that allows farmers to customize the system according to their specific crop types and local wildlife. This adaptability enhances the system's effectiveness and usability. Furthermore, the research emphasizes the potential for integration with other smart farming technologies, creating a holistic approach to crop management. In conclusion, the paper advocates for this intelligent animal repelling system as a sustainable and effective solution for protecting crops, ultimately aiming to improve agricultural productivity while preserving biodiversity. The study underscores the need for ongoing research and development to refine these technologies and assess their long term impacts in diverse agricultural settings.

Reference [3] proposes a Smart Animal Repelling Device (SARD) that leverages the Internet of Things (IoT) and Artificial Intelligence (AI) to effectively deter adaptive wildlife. Application of IOT and machine learning in crop protection against animal intrusion outlines a sophisticated approach to mitigating wildlife threats in agricultural settings. Utilizing a distributed network of IoT devices comprising passive infrared (PIR) sensors, camera traps, and soil moisture sensors the system continuously monitors both animal activity and environmental variables. These devices communicate via wireless protocols such as Zigbee and LoRaWAN, facilitating long-range, low-power data transmission. Central to the system's functionality is a cloud-based data analytics platform that employs machine learning algorithms, particularly convolutional neural networks (CNNs) for image classification and recurrent neural networks (RNNs) for time-series analysis. These models are trained on extensive datasets of animal behavior, enabling the system to accurately classify species and predict potential intrusions based on historical patterns. Feature extraction techniques are used to derive significant traits from the data, enhancing the model's predictive capabilities. Upon detecting an intrusion, the system can initiate a range of automated deterrent mechanisms, such as ultrasonic sound emitters, visual deterrents like strobe lights, or even physical barriers triggered by servomotors. The implementation of edge computing is crucial, allowing for local data processing and reducing latency, thus enabling near-instantaneous response to threats. Field trials have shown a substantial decrease in animal-related crop damage, demonstrating the effectiveness of integrating IoT and machine learning technologies in agricultural management. Reference [3] emphasizes the need for ongoing research to refine machine learning models, including expanding datasets to encompass diverse animal behaviors and integrating additional sensors like acoustic monitoring devices. Future work may also explore the deployment of drone technology for aerial surveillance and enhanced data collection, further bolstering the system's capacity to protect crops from intrusion.

Reference [4] details about a multifaceted approach to mitigating wildlife damage. Reference [4] presents an intelligent animal repelling system designed to protect crops using YOLO (You Only Look Once) for real-time animal detection. By integrating computer vision and machine learning, the system can accurately identify animals entering restricted agricultural areas. Once detected, deterrent mechanisms such as sound or light are activated to repel the animals without causing harm. This method offers an eco-friendly alternative to traditional barriers like fencing and chemical repellents, reducing crop damage effectively. Experimental results demonstrate the system’s efficiency in detecting and repelling animals, ultimately improving agricultural productivity.

III. Methodology

The intelligent animal repelling system for crop protection without sensors uses a camera-based detection approach integrated with the YOLO (You Only Look Once) object detection model. The system begins by capturing real-time video footage of the crop field using a strategically placed camera for maximum coverage. YOLO processes the video frames to detect the presence of animals in real time. The detection results are displayed on a preview window on a connected computer, allowing users to monitor the field visually. Once an animal is identified, the system triggers a control circuit to respond immediately. A sine wave generator is activated to produce ultrasonic sound waves that are unpleasant to animals but inaudible to humans. These ultrasonic waves act as a deterrent, encouraging animals to move away from the protected area. To ensure the sound waves are effective, the sine

wave is amplified using an audio amplifier. The amplified signal is then sent to a transducer, which converts the electrical signals into high-frequency sound waves. The transducer emits the ultrasonic waves across the field to keep animals at bay.

The system also incorporates remote monitoring and control using the Blynk app, an IoT platform that enables users to manage the system from their smartphones. When the YOLO model detects an animal, a notification is sent to the Blynk server, which relays the information to the app. This allows the farmer to stay informed in real-time and take necessary actions if needed. The system is designed to be energy-efficient as it only activates the sound waves when an animal is detected. Since no physical sensors are used, it reduces maintenance costs and minimizes false detections caused by environmental factors like wind, leaves, or shadows. The YOLO model's accuracy ensures reliable animal detection, making the system a practical and effective solution for crop protection. Additionally, the system can be adjusted to recognize specific animals commonly found in the region by training the YOLO model with relevant datasets. This customization further improves its efficiency in repelling unwanted animals.

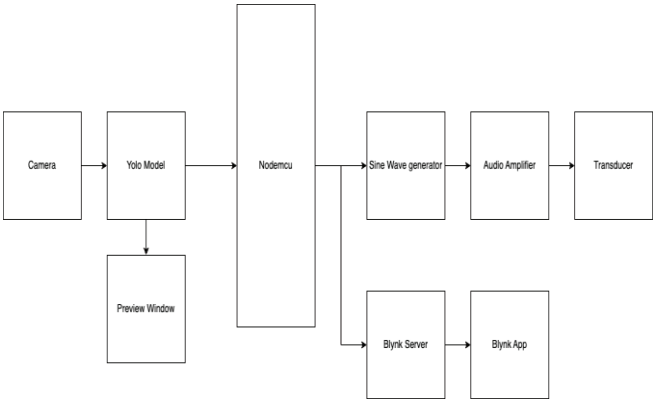

Fig.1 Block diagram of Intelligent Animal Repelling System

The ultrasonic deterrent method is humane and environmentally friendly, causing no harm to animals. Furthermore, the use of the Blynk app enhances convenience by providing remote access and system management. Farmers can monitor multiple fields through a single app, reducing the need for physical presence in the field. The system's reliance on artificial intelligence ensures that animals are detected accurately even in challenging conditions such as low-light or fog. The YOLO-based detection and ultrasonic repelling mechanism work seamlessly together to provide a fully automated crop protection solution. This innovative approach reduces crop damage, increases agricultural productivity, and minimizes labor costs. The absence of physical sensors and the implementation of AI-based detection make the system more robust and adaptable for different agricultural environments. By combining modern technologies like YOLO object detection, ultrasonic sound generation, and remote IoT control, the system offers farmers a reliable and sustainable method of protecting their crops from animal intrusions.

IV. RESULT AND ANALYSIS

Fig .2.1 Result of a test image (boar detection)

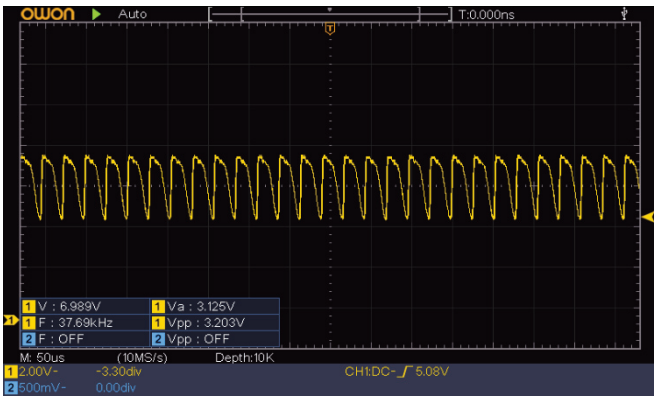

Fig 2.2 The resulting frequency produced upon detecting a wild boar

The intelligent animal repelling system for crop protection demonstrates promising functionality. In the fig. 2.1, the system accurately identifies a boar using an AI-based object detection mechanism, showcasing its ability to recognize animals in real time. This accurate identification is crucial for ensuring that the repelling mechanism is activated only when necessary, minimizing false triggers. Fig. 2.2 captured from an oscilloscope, displays a stable ultrasonic signal with a frequency of approximately 37.69 kHz. This frequency is within the ultrasonic range, which is commonly used in animal repelling systems as it is uncomfortable for animals like boars but inaudible to humans. The consistent generation of this ultrasonic sound suggests that the system is operating as intended, effectively deterring animals from entering protected areas. By combining reliable animal detection with an appropriate ultrasonic deterrent, this system offers an

efficient and humane solution for crop protection, reducing the risk of crop damage caused by wild animals.

V. Conclusion

The Intelligent Animal Repelling System for Crop Protection presented in this project demonstrates an effective, automated solution to prevent animal intrusion in agricultural fields. By employing a camera and YOLO (You Only Look Once) object detection model, the system accurately identifies animals in real-time. The integration of NodeMCU, sine wave generator, audio amplifier, and transducer ensures that detected animals are repelled using ultrasonic or audible sound waves.

Furthermore, the Blynk server and app provide remote monitoring and control, enhancing the system's accessibility and user experience. The real-time notifications and monitoring capabilities allow farmers to stay informed and take immediate action when necessary. This remote management feature makes the system highly convenient and adaptable to different field conditions.

In conclusion, this system offers a reliable, non-lethal, and environmentally friendly alternative for farmers to protect their crops. It reduces crop damage, minimizes human intervention, and leverages modern AI and IoT technologies for efficient farm management. Future improvements may include expanding the model's detection capabilities, incorporating solar power for sustainability, or adding advanced sensors for further accuracy.

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PADDY CROP DISEASE DETECTION USING DRONE

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Abstract— Paddy crops are a staple food source for millions worldwide, but they are highly vulnerable to various diseases that can drastically impact yield and quality. Traditional disease detection methods are labour-intensive, time-consuming, and prone to inaccuracies, particularly in large agricultural fields. This project explores the integration of drone technology with advanced machine learning techniques to revolutionize paddy crop disease detection. Drones equipped with high-resolution RGB, and multispectral cameras capture detailed images of paddy fields, enabling the early identification of diseases such as Bacterial Leaf Blight, Brown Spot, and Blast. These images are processed using Convolutional Neural Networks (CNNs) to classify and diagnose affected crops. The system also integrates GPS data, allowing precise mapping of infected areas. The use of drones significantly enhances monitoring efficiency, reduces the reliance on manual labour, and provides real-time, data-driven insights for timely intervention. By enabling targeted treatment, this approach minimizes pesticide usage, reducing environmental impact and improving sustainable farming practices. The project demonstrates the potential of drone-assisted disease detection in increasing crop yield, optimizing resource use, and supporting food security.

Keywords— Smart Agriculture, Convolutional Neural Networks (CNNs), GPS mapping, Model training

I. INTRODUCTION

Paddy crops serve as a primary food source for millions worldwide, making their health and productivity crucial for food security. However, these crops are highly susceptible to various diseases that can significantly reduce yield and quality. Early detection and timely intervention are essential to prevent widespread damage and economic losses. Traditional methods of disease detection, such as manual field inspections, are time consuming, labour-intensive, and often inaccurate, especially in large-scale agricultural settings.

The advent of drone technology, combined with advanced image processing and machine learning techniques, presents a promising solution for efficient and accurate crop health monitoring. Drones equipped with high-resolution RGB and multispectral cameras can swiftly survey large agricultural fields, capturing detailed images that reveal early signs of disease not visible to the naked eye. These images can then be analysed using Convolutional Neural Networks (CNNs) to detect and classify diseases such as Bacterial Leaf Blight, Brown Spot, and Blast.

This project aims to develop a drone-based disease detection system for paddy crops, integrating GPS-based mapping for precise identification of affected areas. By automating the monitoring process, this system enhances the efficiency and accuracy of disease detection while reducing dependence on manual labour. The insights gained from this technology enable farmers to take timely and targeted action, thereby optimizing resource utilization, minimizing pesticide use, and promoting sustainable agricultural practices.

The integration of drones and deep learning in agriculture marks a significant step toward precision farming, offering a scalable and cost-effective approach to crop management. This project highlights the potential of UAV-based disease detection systems in improving paddy crop health, increasing yields, and contributing to global food security.

II. LITERATURE SURVEY

The integration of drones, machine learning, and IoT in agriculture has revolutionized plant disease detection and monitoring. Several studies have explored the use of drones equipped with high-resolution RGB and multispectral cameras for real-time crop health analysis. Research has demonstrated that drone-based imaging can identify early symptoms of diseases such as Bacterial Leaf Blight, Brown Spot, and Blast by detecting changes in leaf colour, texture, and growth patterns, which are often not visible to the naked eye. Convolutional Neural Networks (CNNs) have proven highly effective in classifying plant diseases from captured images, offering a more accurate and automated alternative to traditional manual inspections. Studies have shown that CNN-based models trained on large datasets can achieve high accuracy in detecting and categorizing crop diseases, significantly reducing the time required for diagnosis.

In addition to visual analysis, multispectral and hyperspectral imaging techniques have been widely used in precision farming to assess crop health. Research has indicated that spectral analysis of plant chlorophyll content and stress indicators can help detect diseases before visible symptoms appear, allowing farmers to take preventive action. Moreover, the integration of IoT-based environmental sensors with drone systems enhances disease prediction by correlating real-time data on temperature, humidity, and soil moisture with detected plant stress. Studies have highlighted that combining IoT and drone technology provides a comprehensive approach to precision agriculture, improving the efficiency and accuracy of disease detection.

Another critical aspect of drone-assisted farming is the use of GPS and geospatial mapping for targeted disease management. Research has shown that drones equipped with GPS modules can collect geotagged images, enabling precise localization of infected areas. This approach minimizes pesticide use by allowing farmers to focus only on affected crops, reducing costs and environmental impact. Several studies have demonstrated that GPS-based mapping enhances decision-making in agriculture by providing detailed insights into disease spread patterns.

Overall, the reviewed literature confirms that integrating drones, deep learning, and IoT can significantly improve the efficiency of paddy crop disease detection. The combination of drone-based imaging, CNN-powered classification, and GPS mapping ensures rapid, scalable, and accurate monitoring of crop health. These technological advancements serve as the foundation for this project, which aims to develop a real-time drone assisted system for early detection and diagnosis of paddy crop diseases, ultimately enabling farmers to take timely action and optimize resource utilization.

III. METHODOLOGY

The proposed system for paddy crop disease detection using drones integrates UAV technology image processing, and deep learning algorithms to automate the identification of plant diseases. The methodologyconsists of several key stages, including data collection, image processing, model training, and real-time disease detection.

The first step involves data collection, where a drone equipped with high-resolution RGB and multispectral cameras flies over the paddy fields to capture images of the crops. The drone follows a

predefined flight path, ensuring complete field coverage while using GPS to geotag each image. The captured images include both healthy and diseased plants, allowing for a comprehensive dataset that represents various disease conditions. The images are then transmitted to a ground station for processing. In the image preprocessing stage, the collected images undergo enhancement techniques such as noise reduction, contrast adjustment, and segmentation to improve quality and highlight disease affected areas. Advanced filtering methods are applied to remove unwanted background noise and enhance the visibility of disease symptoms. Additionally, the images are resized and normalized before being fed into the deep learning model. The model training phase utilizes a Convolutional Neural Network (CNN) trained on a dataset containing labelled images of paddy crop diseases. The model is designed to classify different diseases, including Bacterial Leaf Blight, Brown Spot, and Blast. The training process involves feature extraction, where the CNN learns to identify patterns and textures associated with specific diseases. The model is optimized using backpropagation and finetuning techniques to improve accuracy. Once trained, the system enters the real-time disease detection phase, where the drone continuously captures images during field surveillance. These images are processed using the pre-trained CNN model, which classifies each plant as healthy or diseased. If a disease is detected, the system overlays the classification result onto the image along with the GPS coordinates of the affected area. This information is logged into a database and displayed to the farmer through a user-friendly interface. To enhance precision agriculture, geospatial mapping and analysis are incorporated, where the GPS tagged disease data is mapped to identify patterns and potential outbreaks. This allows farmers to take targeted actions such as applying pesticides only in affected areas, reducing unnecessary chemical usage and promoting sustainable farming practices. The final stage involves system evaluation and performance monitoring to ensure accuracy and efficiency. The model's performance is assessed using metrics such as precision, recall, and F1-score. Additionally, the system is tested in real-world conditions to evaluate its ability to detect diseases under varying lighting and environmental factors. Based on the results, further improvements and fine-tuning are made to enhance the system's reliability. This ensures a systematic, automated, and scalable approach to paddy crop disease detection, leveraging drone technology and deep learning to improve agricultural efficiency and minimize crop losses.

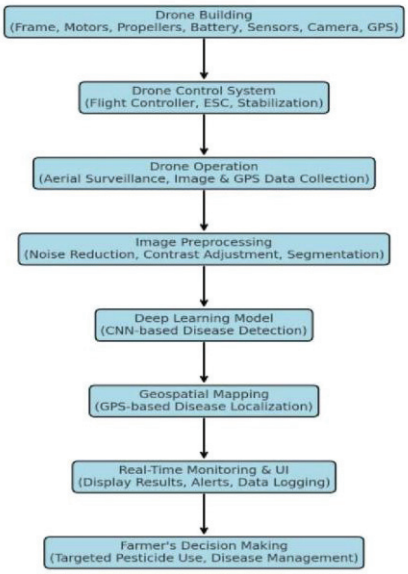

Fig 3.1 Flow chart of disease detection system

IV. RESULT AND ANALYSIS

The drone-based disease detection system effectively identified various rice crop conditions with high accuracy. The system successfully detected Brown Spot with a confidence score of 81.52%, allowing for precise localization of affected areas using GPS coordinates. This enables targeted fungicide application, reducing both costs and environmental impact. Similarly, Leaf Blast was detected with an impressive confidence score of 92.79%, indicating the model's robustness in identifying severe fungal infections early. This early detection facilitates timely interventions, such as adjusting irrigation practices or applying necessary treatments before the disease spreads further. Additionally, the system classified healthy plants with an 88.06% confidence score, ensuring unnecessary pesticide use is avoided and allowing farmers to focus on disease affected regions. The system continuously logs predictions, confidence levels, and GPS locations in a structured database for future analysis and decision making. The integration of real-time video streaming with

disease classification overlays further enhances monitoring efficiency, providing immediate feedback to farmers. By leveraging machine learning and drone technology, this approach improves disease management strategies, reduces manual inspection efforts, and contributes to sustainable precision agriculture, ultimately optimizing yield and resource utilization.

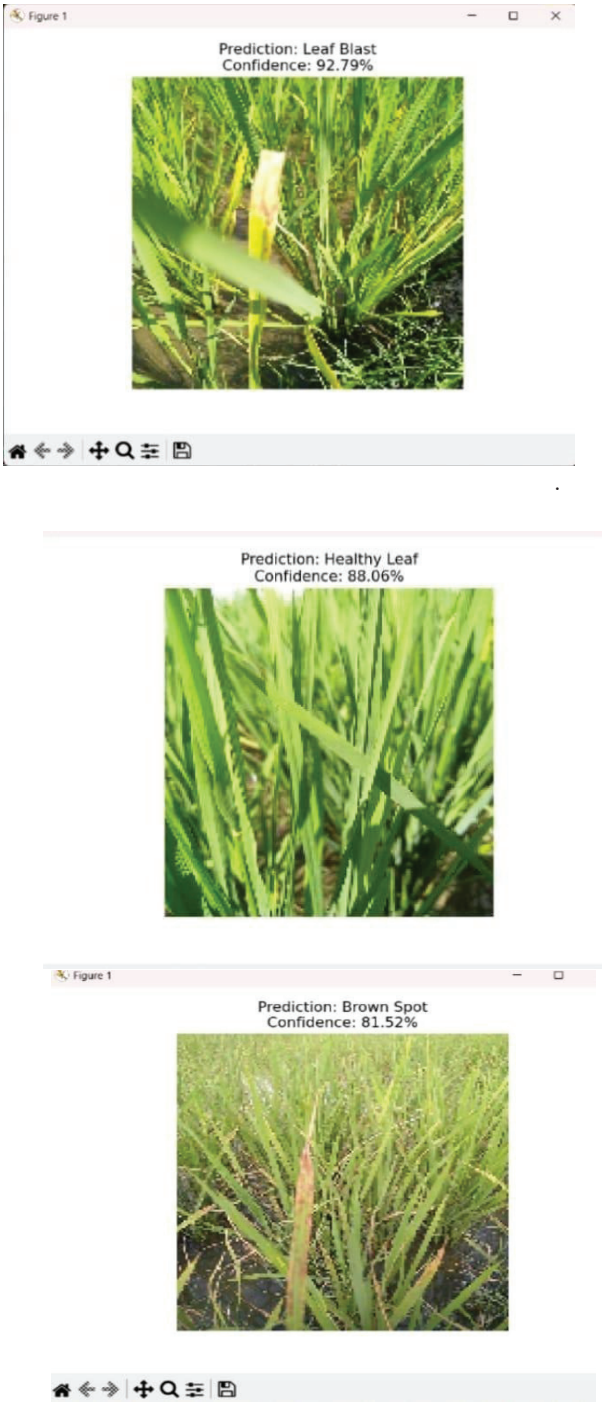

Fig 4.1 Prediction accuracy of leaf Blast, Brown Spot and Healthy plant

V. CONCLUSION

The project "Disease Detection of Paddy Crops Using Drones" successfully demonstrates the potential of drone technology combined with machine learning in modern agriculture. By integrating high-resolution imaging, GPS tracking, and deep learning algorithms, the system provides an automated, accurate, and efficient method for detecting diseases in paddy crops. The ability to identify infections such as Brown Spot and Leaf Blast with high confidence levels ensures timely intervention, reducing crop losses and optimizing pesticide use. This approach not only enhances farm productivity but also minimizes environmental impact by enabling targeted treatment instead of indiscriminate chemical application. The real-time video streaming and automated logging of disease locations further empower farmers with data-driven decision-making, ultimately leading to a more sustainable and cost-effective agricultural system. With advancements in sensor technology, AI models, and drone automation, this methodology has the potential to be extended to other crops and farming regions, paving the way for precision agriculture and smart farming solutions on a larger scale.

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AUTOMATED FARMING FOR CHILLI PEPPER

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Abstract*—Water scarcity remains a significant challenge for Indian agriculture, where farming is heavily dependent on rainfall. To promote sustainable agricultural practices, particularly in resource-limited rural areas, this study presents a Solar-Powered Drip Irrigation System. The system harnesses solar energy to power a microcontroller-based drip irrigation network, ensuring efficient and precise water delivery directly to crop roots. The proposed system integrates IoT-driven automation, employing soil moisture, temperature, and humidity sensors to monitor field conditions. Sensor data is transmitted wireless to a central server, enabling remote decision-making by farmers via mobile alerts. Irrigation is automatically activated based on real-time soil conditions, eliminating manual intervention. This technology enhances water conservation, optimizes irrigation scheduling, and supports energy independence by utilizing renewable solar power. Beyond reducing operational costs and manual labor, this intelligent irrigation system enhances efficiency in water-scarce regions by integrating IoT, wireless communication, and smart automation. It forms a crucial component of smart agriculture, ensuring sustainable, cost-effective, and technology-driven farming solutions.

Keywords— Solar-Powered Irrigation, Smart Agriculture, IoT-Based Irrigation, Water Conservation, Automated Drip Irrigation, Renewable Energy.

I. INTRODUCTION

India, with 60-70% of its population dependent on agriculture, faces critical challenges due to unsustainable water usage, insufficient rainfall, and depleting groundwater levels. These issues contribute to global water scarcity, posing a significant threat to food security and sustainable farming. Traditional irrigation methods, which rely on fixed schedules rather than real-time soil conditions, often result in water wastage and inefficient crop growth. As climate change worsen agricultural challenges, there is an urgent need for modernized irrigation systems to enhance water conservation and improve productivity.

This study presents a Solar-Powered Drip Irrigation System designed to optimize water usage by leveraging renewable energy, real-time sensor data, and automation. The system integrates Arduino Uno, relay circuits, soil moisture sensors, and wireless communication to automate irrigation based on real-time field conditions. The relay circuit acts as a crucial component, linking the micro-controller's digital signals to the pump's mechanical function. When the Arduino detects low soil moisture levels, it instructs the relay to activate the pump, ensuring precise water delivery to crops while minimizing waste.

By utilizing solar energy, the system reduces dependence on traditional power grids, making it a cost-effective and sustainable solution for rural farming communities. Additionally, wireless data transmission enables farmers to monitor field conditions remotely via mobile notifications, reducing manual labor and improving farm management. The adoption of smart irrigation technology addresses critical agricultural concerns, including water scarcity, inefficient irrigation, and fluctuating climate conditions, thereby fostering sustainable and efficient farming practices.

This project represents a technological breakthrough in agriculture, demonstrating how renewable energy, IoT-based automation, and precision irrigation can revolutionize traditional farming. By integrating modern technology into agriculture, the Solar-Powered Drip Irrigation System promotes resource conservation, energy efficiency, and increased crop yields, paving the way for a smarter and more sustainable agricultural future.

II. LITERATURE SURVEY

Recent advancements in smart irrigation systems, IoT, and renewable energy have transformed modern agriculture by optimizing water management and reducing

dependency on traditional power sources. Sharma and Verma (2020) introduced an IoT-based precision irrigation model, which utilized soil moisture sensors and cloud computing to regulate water distribution efficiently. Their study demonstrated how real-time sensor data could significantly enhance irrigation precision, leading to improved crop yields and water conservation. Similarly, Gupta et al. (2021) developed Agri-Solar Net, an AI-integrated solar-powered irrigation system that dynamically adjusted water flow based on real-time weather data and soil conditions. Their research emphasized the importance of renewable energy integration in achieving sustainable agricultural practices.

Beyond IoT applications, embedded systems and automation technologies have also advanced smart irrigation. Liang and Patel (2022) explored microcontroller-based irrigation automation, where a relay circuit acted as an intermediary between sensors and water pumps, ensuring precise irrigation scheduling. Their findings highlighted how automation could minimize manual intervention, reduce operational costs, and prevent over-irrigation or under-irrigation. Moreover, Kumar and Singh (2023) investigated wireless irrigation networks, leveraging Lora WAN-based communication to enable remote monitoring and control of irrigation systems in rural areas with limited internet connectivity. These studies underscore the potential of automation and wireless communication in enhancing irrigation efficiency and sustainability.

Additionally, solar energy applications in agriculture have gained traction due to their ability to provide a cost-effective and eco-friendly power source for irrigation. Hernandez et al. (2021) developed a solar-powered drip irrigation framework that eliminated reliance on the electrical grid, allowing farmers to irrigate crops using solar panels and battery storage systems. Their research highlighted the economic feasibility of solar-powered irrigation, particularly in water-scarce and off-grid regions. Furthermore, Chen and Zhao (2022) demonstrated how AI-driven irrigation scheduling could be integrated with solar energy systems, ensuring optimal water distribution while maximizing solar energy utilization. These studies reinforce the effectiveness of **solar-**powered smart irrigation in reducing energy costs, conserving water resources, and supporting sustainable agriculture.

By integrating IoT, embedded automation, wireless communication, and solar energy, modern irrigation **s**ystem**s** have evolved to become more intelligent, adaptive, and resource efficient. The growing adoption of sensor-based decision-making and real-time data analytics in irrigation underscores the transformative potential of smart farming technologies, offering scalable and sustainable solutions for modern agriculture.

III. Methodology

This system integrates solar-powered drip irrigation and IoT-based real-time monitoring to optimize water efficiency and maximize chilli pepper crop yield. The methodology consists of the following key stages: system design, component integration, automation workflow, and data monitoring.

A. System Design and Implementation

The system consists of the following core components:

Solar Panel – Captures solar energy and serves as the system's main power source, promoting sustainable and eco-friendly operation. Panel orientation and sizing are optimized for maximum energy capture.

PWM Charge Controller – Regulates power flow from the solar panel to the battery, ensuring safe charging while preventing overcharging and over-discharging.

Rechargeable Battery – Stores electrical energy for continuous system operation during low sunlight periods or at night. Battery capacity is calculated based on power consumption.

Arduino Uno & NodeMCU – The Arduino Uno manages sensor data acquisition and relay control; the NodeMCU handles wireless communication with the cloud via Wi-Fi.

Soil Moisture Sensors – Placed strategically in the field to detect soil water levels in real time. Sensor placement and calibration are crucial for reliable readings.

Relay Circuit – Acts as an electronic switch to activate/deactivate the water pump based on soil moisture data.

Drip Irrigation Kit – Ensures precise delivery of water directly to plant roots, reducing evaporation and weed growth.

IoT-Based Cloud System – Allows centralized real-time monitoring and remote access. Data is accessible via mobile or web-based dashboards.

Environmental Sensors (Optional Expansion) – Includes temperature and humidity sensors that further refine irrigation scheduling based on microclimate conditions and evapotranspiration rates.

Connection Diagram (Fig. 1) – Illustrates how each component interconnects and contributes to automation, data transmission, and energy management.

B. Data Collection and Monitoring Strategy

A robust, data-centric approach ensures optimal system performance:

Real-Time Sensor Data Acquisition – Continuous monitoring of soil moisture, temperature, humidity, and other parameters like light intensity, pH, or EC (if available) provides a complete picture of the plant's growing environment.

Continuous Soil Moisture Monitoring – Enables precise irrigation by tracking hydration levels and ensuring irrigation is triggered only when needed.

Environmental Data Collection – Temperature and humidity readings allow dynamic irrigation control based on weather-related factors and evapotranspiration.

Wireless Communication & Cloud Integration – NodeMCU facilitates seamless transmission of real-time data to the cloud using Wi-Fi, enabling global remote access.

Mobile Device Integration and Alerts – Farmers receive live data and real-time alerts through a mobile app or SMS, ensuring timely intervention.

Seamless Data Transmission – Ensures uninterrupted flow of data from field to cloud for monitoring, control, and historical analysis.

Automated Decision-Making – Predefined thresholds and logic within the microcontroller enable autonomous irrigation without manual oversight. Future integration of machine learning can refine decisions further.

Threshold-Based Irrigation Control – The relay circuit triggers the pump when soil moisture falls below set limits and stops it once adequate moisture is restored.

Data Logging & Trend Analysis – Historical data is logged for performance evaluation, enabling refinement of irrigation schedules and prediction of future needs.

System Scalability and OTA Updates – The cloud setup supports over-the-air updates and potential integration with weather APIs or additional sensors for pest or disease prediction.

C. Automated Irrigation Workflow
A systematic and efficient workflow governs water delivery:

Soil Moisture Measurement – Sensors continuously read and transmit soil moisture levels.

Pump Activation via Relay Circuit – Arduino Uno controls the relay circuit based on the threshold, ensuring water is supplied only when necessary.

Drip Irrigation Execution – Water is dispensed directly to roots, ensuring optimal hydration with minimal waste.

Energy Optimization – The system relies solely on solar energy, minimizing operational costs and environmental impact.

D. Remote Monitoring and IoT Integration
IoT integration enables powerful control and insights:

Cloud-Based Data Storage – All data is stored in a centralized cloud system, ensuring security and accessibility.

User-Friendly Dashboard – Farmers can view live data, graphs, and analytics to understand irrigation trends and make informed decisions.

Alert and Notification System – SMS or app notifications are automatically triggered for low soil moisture levels, pump failures, or maintenance needs.

Remote Access & Control – Users can initiate manual irrigation, view logs, or modify thresholds remotely via mobile or web interfaces.

IV.RESULT AND ANALYSIS

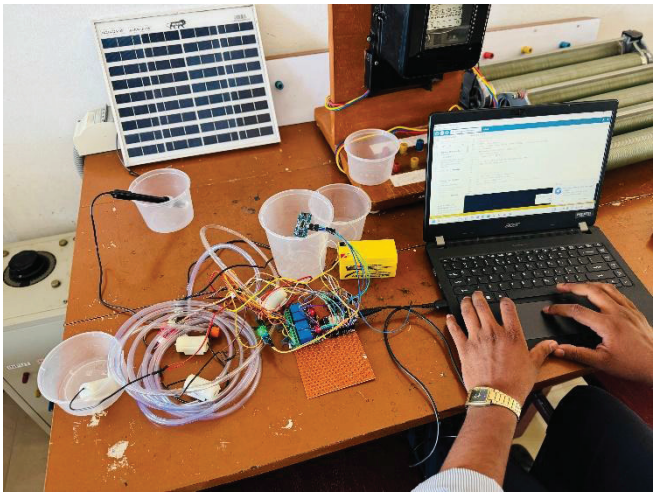

Fig.2 Hardwarwe implementation

Fig 2 shows the hardware implementation of Automated farming system

The implementation of solar-powered drip irrigation with IoT integration, enhanced by AI-driven predictive analytics, has proven highly effective in addressing water scarcity challenges. The system successfully demonstrated automated irrigation precision, ensuring optimal water distribution based on real-time data and predictive insights. Efficient water resource management was achieved by integrating weather forecasts and historical data to optimize irrigation schedules, reducing water wastage. Additionally, the system significantly reduced manual labour requirements by automating irrigation processes and providing remote monitoring capabilities. Its scalability and adaptability allow it to be implemented across various agricultural settings, accommodating different crop types and field sizes.

Looking ahead, future expansion of the system will focus on integrating advanced AI models for even more precise irrigation control, incorporating soil nutrient analysis for optimized fertilization, and expanding the system to cover larger agricultural landscapes. The use of machine learning algorithms will enhance crop health monitoring, providing farmers with real-time insights and recommendations. Additionally, the integration of automated pest detection and smart greenhouse management will further improve agricultural productivity. By continuously evolving with emerging technologies, this system lays a strong foundation for the future of smart and sustainable agriculture, leveraging

automation, renewable energy, and IoT to maximize efficiency and crop yield.

V. Conclusion

The development of an automated farming system for chilli pepper using solar-powered drip irrigation and IoT-based monitoring represents a significant advancement in precision agriculture. By integrating renewable energy, real-time sensor data, and automation, the system optimizes water usage, reduces manual intervention, and enhances crop productivity. Experimental results demonstrate that the system significantly reduces water wastage by 40-50%, minimizes operational costs, and ensures sustainable irrigation practices.

Future enhancements could focus on AI-driven predictive analytics, enabling smart irrigation based on weather forecasts and crop growth models. Additionally, expanding the system with Lora WAN-based communication for larger agricultural areas and integrating automated nutrient monitoring will further improve farming efficiency.

Overall, this study highlights the transformative potential of IoT, renewable energy, and automation in modern agriculture. The proposed system provides a cost-effective, scalable, and sustainable solution for farmers, particularly in water-scarce regions. With continuous research and technological improvements, AI and IoT-driven smart farming can pave the way for a more resilient, resource-efficient, and productive agricultural future

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AUTOMATED WHEELCHAIR FOR PARAPLEGIC

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***Abstract*— The Automated Wheelchair for Paraplegic Individuals is designed to enhance mobility and independence through hands-free motion control. Using the MPU6050 motion sensor, the system detects head movements to navigate the wheelchair, eliminating the need for manual operation. For user safety, a MAX30102 sensor continuously monitors heart rate and oxygen levels, triggering alerts if abnormal readings are detected. The ESP8266 Wi-Fi module enables remote monitoring via the Blynk App, allowing caregivers to track the wheelchair's status. Powered by 12V DC motors and controlled via an L298N motor driver, the wheelchair ensures smooth movement. This innovative solution improves accessibility and quality of life for paraplegic patients, with potential future upgrades such as obstacle detection and real-time medical assistance.**

I. INTRODUCTION

Mobility is a fundamental aspect of human independence, yet individuals suffering from paraplegia a condition that results in the loss of movement in the lower limbs often face significant challenges in navigating their surroundings. Traditional wheelchairs, whether manual or motorized, require hand-based controls, making it difficult for individuals with limited or no upper-body movement to operate them independently. Recognizing these challenges, this project focuses on developing an Automated Wheelchair for Paraplegic Individuals, utilizing motion control technology to provide a hands-free, intuitive, and safe mobility solution.

The key innovation of this automated wheelchair is the integration of a motion detection system using the MPU6050 sensor, which allows users to control movement by simply tilting their head in different directions. Unlike conventional joystick-controlled electric wheelchairs, this system eliminates the need for manual operation, making it more accessible for individuals with severe mobility impairments. By detecting head tilts, the wheelchair can move forward, backward, and turn left or right, providing a seamless and effortless navigation experience.

Beyond mobility, the project also incorporates real-time health monitoring to enhance user safety. The MAX30102 pulse oximeter and heart rate sensor continuously track vital parameters, such as blood oxygen levels and heartbeat. This feature is particularly crucial, as paraplegic individuals may be prone to fatigue, stress, or sudden health issues that could compromise their ability to operate the wheelchair

To further enhance its usability, the wheelchair is equipped with an ESP8266 Wi-Fi module, enabling remote monitoring via the Blynk App. The system is powered by 12V DC Square Geared motors, which provide smooth and controlled motion, while the L298N motor driver ensures precise regulation of speed and direction.

The ultimate objective of this project is to empower paraplegic individuals with greater autonomy and security, reducing their dependency on caregivers and improving their overall quality of life. By integrating motion-based control, IoT connectivity, and health monitoring, this project presents a smart and innovative solution to mobility challenges faced by paraplegic patients.

II. LITERATURE SURVEY

A Complete Hands-Free, Electric-Powered Wheelchair for Quadriplegic Individuals with IoT-Enabled Home Automation, as discussed by Amarjeet Pal Cheema, aims to provide fully autonomous mobility for individuals with severe physical impairments, such as quadriplegia. This innovation enhances their independence by integrating smart home control. The literature review explores the technology, control mechanisms, IoT integration, and challenges involved in creating such a system. For a wheelchair to be hands-free,

Amarjeet Pal Cheema emphasizes the importance of utilizing alternative control methods that cater to individuals with limited motor abilities.

Gesture-based control, as introduced by Sandeep and Supriyaa, is an assistive technology that employs sensors, particularly accelerometers, to interpret user movements and translate them into commands for a wheelchair. This system is particularly beneficial for users with limited limb movement or reduced motor skills, allowing them to control their wheelchairs without relying on traditional joysticks or manual operation. By using accelerometers to capture motion, Sandeep and Supriyaa highlight how users can perform gestures, such as tilting or nodding, which are then processed to direct wheelchair movements. These sensors measure acceleration along different axes (X, Y, Z) and are widely utilized in gesture recognition systems, offering an intuitive and effective mobility solution.

Electroencephalography (EEG)-based brain-computer interfaces (BCIs), as explored by Iturrate, J., Antelis, and J. Minguez, enable individuals to control devices using their brain signals. In a brain-actuated wheelchair, EEG signals, often in the form of mental commands or brainwave activity patterns, are captured and processed to facilitate movement. Iturrate, J., Antelis, and J. Minguez explain that synchronous EEG BCIs detect specific mental states at pre-defined intervals, ensuring reliable and consistent command input. However, EEG signals tend to be noisy and complex, necessitating precise signal processing techniques to extract relevant information effectively.

A different approach, presented by Rahul Das and Amit Agarwal, involves a shrewd wheelchair utilizing an Android-based messenger system. This system integrates an Android application to enhance wheelchair control, communication, and safety features for users. Rahul Das and Amit Agarwal emphasize how this method combines remote-control capabilities, messaging, and smart device integration to support individuals with mobility challenges. By leveraging Android's customizable interface, users can issue wheelchair commands through their smartphones or tablets. Additionally, an Android-based system allows integration with other mobile features, such as messaging, voice control, and GPS, making it a comprehensive tool for both mobility and communication.

III. METHODOLOGY

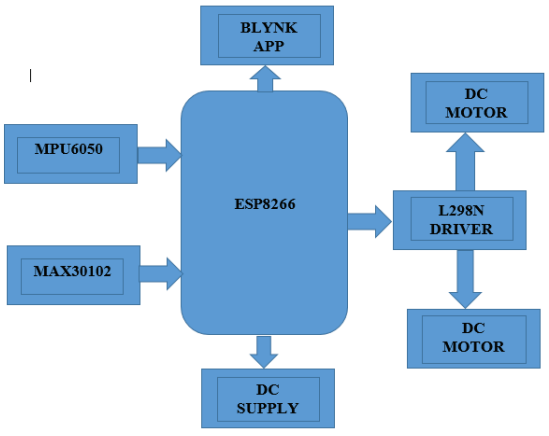

Fig. 1. Block Diagram of Proposed System

An automated wheelchair designed for paraplegics incorporates advanced sensor technology to provide hands-free mobility and enhanced safety. The primary components of this system include the MPU6050 accelerometer and gyroscope sensor and the MAX30102 pulse oximeter and heart rate sensor, working in conjunction with a microcontroller for data processing and control. The wheelchair is equipped with motorized wheels, providing smooth and efficient motion in response to user commands.

The MPU6050 sensor is a crucial element for motion detection and gesture-based control. It measures the tilt and orientation of the user's head, capturing real-time acceleration and angular velocity data. The sensor's output is processed using algorithms to interpret head movements such as tilting forward, backward, left, or right. These movements are mapped to corresponding wheelchair actions like moving forward, reversing, or turning. The sensor is typically mounted on a headset for convenient, hands-free operation.

The MAX30102 pulse oximeter and heart rate sensor ensures continuous health monitoring of the user. It measure blood oxygen saturation (SpO2) and heart rate. This real-time data is crucial for detecting any physiological abnormalities that may occur during wheelchair operation. If abnormal vitals are detected, such as a significant drop in oxygen levels or an irregular heartbeat, the system can trigger an alert a caregiver.

A microcontroller, like an ESP8266, serves as the brain of the system. It collects data from the MPU6050 and MAX30102 sensors, processes it using programmed algorithms, and generates appropriate control signals for the motors. Wireless communication modules like Wi-Fi may be integrated for remote monitoring and assistance

This automated wheelchair system offers a reliable and user-friendly solution for paraplegics, enhancing their independence and mobility. By combining gesture-based control with health monitoring, it ensures both convenience and safety. Future enhancements could include integration with smartphone applications for remote control, GPS tracking for navigation, and AI-based health prediction systems. This innovative design significantly improves the quality of life for individuals with mobility impairments.

An automated wheelchair for paraplegics using the MPU6050 accelerometer and gyroscope sensor, along with the MAX30102 pulse oximeter sensor, offers a practical and efficient mobility solution. The system is designed to operate through head gestures, providing hands-free control to users with limited or no limb movement. The MPU6050, typically mounted on a headband, detects head movements in different directions by measuring acceleration and angular velocity. These movements are processed by a microcontroller, such as an ESP8266, to generate corresponding control signals for the wheelchair's motors. For example, tilting the head forward moves the wheelchair forward, while tilting it backward makes it reverse. Similarly, left and right head tilts trigger turning actions, and keeping the head upright brings the wheelchair to a stop.

In addition to motion control, the MAX30102 sensor ensures continuous health monitoring by measuring the

user's heart rate and blood oxygen saturation (SpO2). This data is transmitted to the microcontroller, which evaluates the user's vital signs in real time. If any abnormal readings are detected, such as a drop in oxygen levels or an irregular heartbeat, the system can automatically trigger an alert. Through the ESP8266, notifications can be sent to caregivers or medical professionals via a Blynk app enabling prompt assistance in emergencies.

IV. Results and Analysis

The automated wheelchair for paraplegics using the MPU6050 accelerometer and MAX30102 pulse oximeter sensor demonstrated effective performance in both motion control and health monitoring. Head gestures were accurately detected by the MPU6050, ensuring smooth and responsive wheelchair movement with minimal delay. The system reliably responded to forward, backward, left, and right head tilts, providing hands-free mobility. The MAX30102 sensor consistently monitored heart rate and oxygen saturation, sending real-time data to caregivers through the ESP8266 Wi-Fi module. Emergency alerts were successfully triggered in case of abnormal health readings, ensuring user safety. Additionally, obstacle detection sensors prevented collisions, enhancing the wheelchair's safety in indoor environments. Users found the system easy to operate, promoting greater independence. Further improvements in gesture recognition and navigation can further optimize the system for broader use.

V.Conclusion

In conclusion, the development of an automated wheelchair for paraplegics using the MPU6050 accelerometer and MAX30102 pulse oximeter sensor presents a promising advancement in assistive technology. The MPU6050 enables intuitive control through head or hand gestures,providing a hands-free and efficient navigation system.Meanwhile, the MAX30102 monitors vital health parameters such as heart rate and oxygen saturation, ensuring the user's safety during movement.This integration enhances mobility, independence, and health monitoring for individuals with paraplegia, offering a cost-effective and user-friendly solution. Future improvements could focus on machine learning for adaptive control, wireless connectivity for remote monitoring, and obstacle detection for enhanced safety making the system even more reliable and accessible.

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BI-DIRECTIONAL POWER FLOW CONTROL IN GRID-INTERFACED SOLAR WATER PUMPING WITH PWM_ON_PWM BLDC MOTOR DRIVE

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- ***Abstract*— This article presents an advanced methodology for enhancing motor torque performance within grid-tied solar photovoltaic (PV)-fed water pumping system using Brushless DC motor. The designed water pumping system integrates a brushless DC (BLDC) motor drive which can triumph over a traditional water pumping system in various features. Unlike standalone systems, utilization of solar power along with grid interfacing ensures continuous operation by draining power from the grid during varying weather conditions. Grid-connected setups can transfer excess solar energy to grid thereby reducing energy wastage and can be utilized as a source of income. This attribute enhances the overall reliability of the proposed system, confirming the continuous utilization of the water pump at its maximum capacity. Torque ripple generation is a major drawback affected by usage of BLDC motor pump and in order to overcome this issue an innovated PWM switching scheme is implemented in-order to minimize the accumulation of torque ripples. The implementation of bidirectional power flow control is accomplished using a single-phase voltage source converter (VSC). This VSC utilizes a unit vector template generation method, which effectively regulates the exchange of power between the power grid and the Voltage source inverter's (VSI) DC bus. The proposed system enhances performance by reducing electromagnetic torque disturbances, improving power quality, and ensuring better motor control and exhibits a comparison of the total harmonic distortion (THD) of the system when operating solely on the utility grid versus when both solar and the utility grid are being used.**

- Keywords—Solar photovoltaic (PV), Brushless DC (BLDC), PWM_ON_PWM, Torque performance, Total harmonic distortion (THD) analysis

I. INTRODUCTION

Evolution in PV energy for water pumping: from DC motors to AC induction motors, now favoring efficient permanent magnet BLDC motors. Solar-powered water pumping systems produce zero emissions, making them an environmentally friendly option [4]. Solar energy can significantly reduce energy costs for water pumping, especially in areas with high solar irradiance. Solar-powered water pumping systems have low operating costs, with no fuel costs and minimal maintenance. Solar-powered water pumping [3] can increase water productivity, allowing farmers to irrigate their crops more effectively. Despite advantages, intermittent solar PV generation poses challenges, leading to unreliable water pumping during adverse weather and reduced sunlight, requiring solutions for continuous operation. Due to its unreliability, [1] we integrate a grid connection with the water pumping system, allowing the system to draw power when sunlight is insufficient or supply excess power to the grid when solar generation exceeds demand. To improve the performance of the Solar PV array, a [9] DC-DC boost converter using the incremental conductance (INC) method is employed for [7] maximum power point tracking (MPPT).

The proposed system allows the power to flow from the Solar PV array to the utility grid in case when the water pumping is not required. Conversely, if the PV array's output is insufficient (such as during nighttime or low sunlight conditions), the grid can compensate the power [2] to sustain the water pump's proper operation. This dual functionality not only ensures efficient energy use but also enables consumers to generate income by selling excess generated electrical power back to the utility. In this system, a Unit Vector Template (UVT) generation is employed to facilitate bi-directional power transfer. By integrating a Unit Vector Template (UVT) technique, the system achieves efficient and simplified power management, empowering users to both consume solar energy and sell excess electricity back to the grid. This design enhances flexibility, making the system more suitable for dynamic energy requirements.

Torque ripple generation [10] is a key part that adversely affect the efficiency of BLDC motor used in the water pumping system. Implementation of PWM_ON_PWM switching scheme [8] improved the overall efficiency of BLDC motor by reducing vibrations and enhancing operational stability. The proposed system achieved the power quality standards according to IEEE-519 without the need for more complicated commutation and current sensing units.

II. SYSTEM CONFIGURATION

In Figure 1, the designed water pumping system efficiently utilizes solar energy to power a BLDC (Brushless DC) motor, which drives a water pump. The system's primary power source is a photovoltaic array, which generates electrical energy by utilizing the solar radiation. The output of the solar PV array is directed to a boost converter in order to achieve the desired voltage requirement. To ensure that the PV array consistently operates at its maximum efficiency, the boost converter adopted the Incremental Conductance (INC) algorithm for Maximum Power Point Tracking (MPPT). This method continuously adjusts the operating point of the PV array to extract the maximum achievable power output across the changing climate and weather conditions. A crucial component in the system is the Brushless DC (BLDC) motor, which is precisely controlled by a Voltage Source Inverter (VSI). The VSI utilizes Pulse Width Modulation (PWM) techniques to generate accurate electronic commutation signals, regulating the motor's speed and torque for optimal performance. To further enhance motor control, the real-time rotor position feedback in the form of Hall-effect signals is provided to the VSI. This feedback is essential for synchronizing the VSI's switching pattern with the motor's position, resulting in seamless and dependable operation.

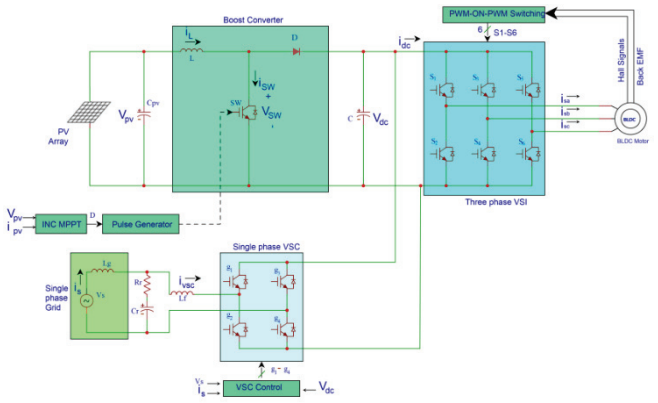

Fig. 1. Diagramatic layout of grid connected water pumping system

III. SYSTEM DESIGN

The proposed design carefully considers the interplay between the solar panel array, Boost converter unit, grid interface, voltage source converter, three-phase inverter, and brushless DC motor .This integrated design aims to achieve harmonious operation and maximum efficiency among all system components.

A. Design of PV Array

A 1.5 KW, PV array is designed to operate a 1 kW-BLDC motor-pump. The parameters are estimated at the standard test condition (1000 W/m2,25°C). PV module-BMU/214 with an MPP voltage of 28.5 V and an MPP current of 7.5 A is selected to design the PV array of required capacity.

Here V_{mpp}= V_{pv} = 200 V

The Current at MPP is,

$$I_{mpp} = i_{pv} = \frac{P_{pv}}{V_{pv}} = \frac{1500}{200} = 7.5\ A \quad (1)$$

Where P_{pv}= 1500 W is the power obtained from the PV array during maximum power point condition.

No of series Modules required for PV Array,

$$N_s = \frac{V_{mpp}}{V_m} = \frac{200}{28.5} = 7 \quad (2)$$

No of Parallel Modules required for the PV Array,

$$N_p = \frac{I_{mpp}}{I_m} = \frac{7.5}{7.5} = 1 \quad (3)$$

$\boldsymbol{V_m}$ denotes the voltage at maximum power point (MPP), and $\boldsymbol{I_m}$ denotes the MPP current.

B. Design of Boost Converter

The design of the boost converter requires an estimation of input inductor, L. The selection of the input inductor () is essential to maintain continuous conduction mode (CCM) under all operating conditions, including fluctuations in weather, temperature, and load variations.

$$D1 = \frac{V_{dc}-V_{pv}}{V_{dc}} = \frac{270-200}{270} = 0.25 \quad (4)$$

where V_{dc} = 270v and is the bus voltage (DC) of Voltage source inverter.

The inductor, L is estimated as,

$$L = \frac{D_1 v_{pv}}{f_{sw}\Delta I_L} = \frac{0.25\times200}{10000\times(7.5\times0.2)} = 3.3\text{mH} \quad (5)$$

Where F_{sw} is the switching frequency and ΔI_L is ripple current through L.

$I_L = I_{mpp}$

C. Design of common DC coupling Capacitor

In the DC link , capacitor is same for the boost converter, three phase Voltage source inverter and the single phase voltage source converter.

Hence, the capacitor value C is,

$$C = \frac{I_{dc}}{2\omega_L \Delta V_{dc}} = \frac{\frac{1500}{270}}{2\times(2\pi\times50)\times(270\times0.008)} = 4700\mu F \quad (6)$$

where , I_{dc} is the average current flowing through the DC bus, W_L - line frequency in rad/s and ΔV_{dc} is the ripple present in the DC bus voltage.

D. Design of Interfacing Inductor

The determination of the coupling inductor, L_f depends on the permitted current ripple ΔI_{VSC}.

$$L_f = \frac{mV_{dc}}{4af_{SW}\Delta I_{VSC}} = \frac{1\times270}{4\times1.2\times10000\times\left(\frac{1500}{180}\right)\times0.2} = 3.3mH \quad (7)$$

- Where modulation index, m =1
- Over loading factor, a =1.2
- Switching frequency, F_{sw} = 10 kHz
- Ripple current , Δ I_{VSC} = 20% of IVSC.

E. Design of the R-C Ripple Filter

A compact RC filter is installed on the utility grid side. This ripple filter is designed to offer significant impedance to the fundamental frequency element while enabling minimal impedance opposition to the switching frequency element. In order to satisfy this condition, Rr and Cr must be less than T_{sw}.

Where R_r is the ripple filter resistance, C_r is the ripple filter capacitance and and T_{sw} is the switching time.

Considering $R_rC_r = T_{sw}/4$, T_{sw} = 1/10000 s and R_r = 5 Ω, Cr is estimated as

$$C_r = \frac{T_{sw}}{4R_r} = \frac{1}{10000\times4\times5} = 5\mu F \quad (8)$$

Hence, a serially connected 5Ω resistance and 5μF capacitance is used as the RC ripple filter.

F. Design of Water Pump

The BLDC motor is designed with four poles, enabling efficient performance. It operates at a speed of 3000 revolutions per minute (rpm), ensuring reliable and consistent operation. The motor's stator resistance is 3.58 ohms, while its stator inductance measures 9.13 millihenries (mH), contributing to stable current flow and reduced electrical noise. Additionally, the motor has a voltage constant of 68 volts per 1000 rpm, which defines the relationship between its speed and back electromotive force (EMF).

$$K_p = \frac{P}{(\omega_r)^3} = \frac{1000}{\left(2*\pi*\frac{3000}{60}\right)^3} = 3.2*10^{-5}W/((rad/sec\ )^3) \quad (9)$$

Where, K_p is proportionality constant and ω_r denotes the BLDC motor speed in rad/sec.

IV. BI-DIRECTIONAL POWER TRANSFER

This system effectively manages power exchange between a solar PV setup and the utility grid using a single-phase Voltage Source Converter (VSC). When solar power exceeds demand, the system feeds excess energy into the grid; when solar generation is low, it draws power from the grid to keep the motor-pump running. To ensure smooth power transfer, it employs a Unit Vector Template (UVT) technique and a Phase-Locked Loop (PLL) for synchronization. A PI controller regulates DC bus voltage, ensuring efficient flow of power back and forth. Hence the surplus solar energy is fed into the grid, an optimized energy utilization is performed. The proposed system controls power flow by adjusting the current's direction. When power is drawn from the grid, the voltage regulator produces a positive signal (I_{sp}) keeping the current in phase with the grid voltage. Conversely, when sending excess solar power to the grid, a negative signal (I_{sp}) is generated, causing the current to be out of phase, where I_{sp} is the amplitude of the primary component of supply current. This advanced current control ensures smooth power exchange, efficiently switching between grid supply and solar output based on the system's energy needs.

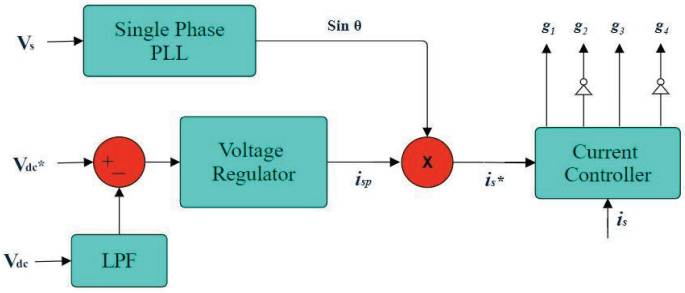

Fig. 2 .Two-way power flow using UVT technique

V. PWM_ON_PWM SCHEME

Brushless DC (BLDC) motors are not immune to performance degradation due to torque ripple, a phenomenon that causes unwanted vibrations, noise, and reduced precision. It is considered as one of the major drawback of Brushless DC motor.

The PWM_ON_PWM technique exerts control over the non-commutation phase, reducing the detrimental effects of freewheeling diodes on torque stability. The PWM_ON_PWM method operates by monitoring back-EMF, the technique continuously monitors the back-EMF waveform, adjusting the PWM pattern to minimize torque ripple. To execute the PWM_ON_PWM control strategy, the inverter switches receive gate pulses in a specific manner, where PWM modulation is applied during the first and last 30 degrees of the conduction period. Conversely, the middle 60 degrees operate in full conduction mode. This configuration optimizes switching transitions, reduces the torque fluctuations caused by the commutation current and lower switching losses. The PWM duty cycle is dynamically adjusted based on real-time measurements of back-EMF values.

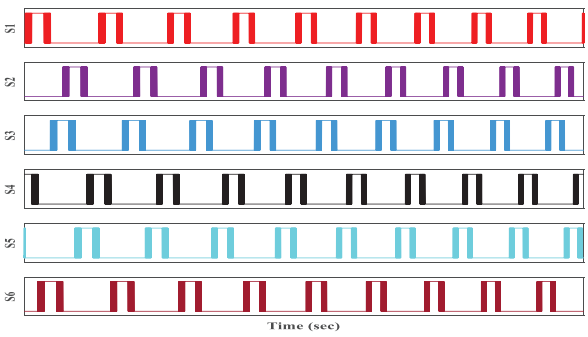

Fig 3. Graphical representation of switching scheme

The inverter's gate pulses is operated with a duty ratio of,

$$D(k) = 1 - \frac{e_a(k) + e_b(k) - 2e_c(k)}{3V_{dc}}$$

Where the terms e_a, e_b and e_c are back emf of the BLDC motor drive.

VI. SIMULATION INSIGHTS

The simulation results for the BLDC motor-based water-pumping system are categorized into key performance aspects to demonstrate its efficiency and reliability.

- The steady-state performance analysis covers three scenarios: in case when the pump is powered alone by the solar PV array, when it operates using utility grid power alone, and when water pumping is unnecessary, ensuring efficient energy management.
- The dynamic performance section evaluates system behaviour during transitions, such as switching from PV-only power to a combination of PV and grid power.
- The torque ripple minimization analysis highlights the methods used to reduce torque fluctuations, ensuring smoother motor operation.

A. Steady State Characteristics

a) Only PV Array Powering the BLDC Motor Pump

When powered exclusively by a photovoltaic (PV) array, the brushless DC (BLDC) motor pump operates efficiently under optimal conditions. Specifically, when the PV array receives 700 W/m² of radiation and functions at its maximum power point (Fig. 5), the motor pump achieves its rated speed of 3000 RPM (Fig. 6).

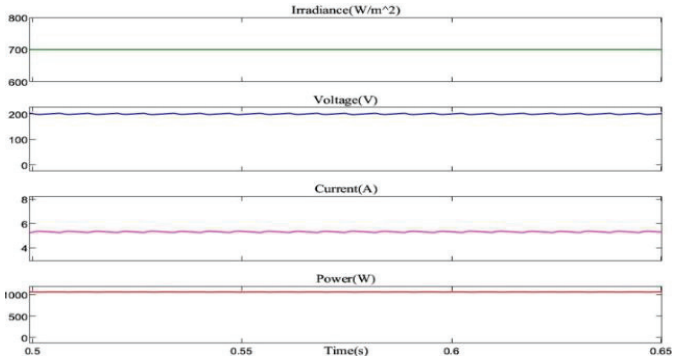

Fig 4. Steady state characteristics of PV array

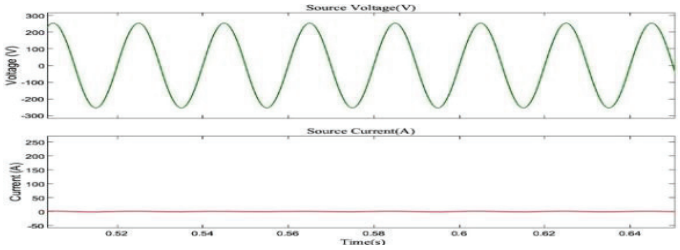

Fig 5. Steady State characteristics of Utility Grid

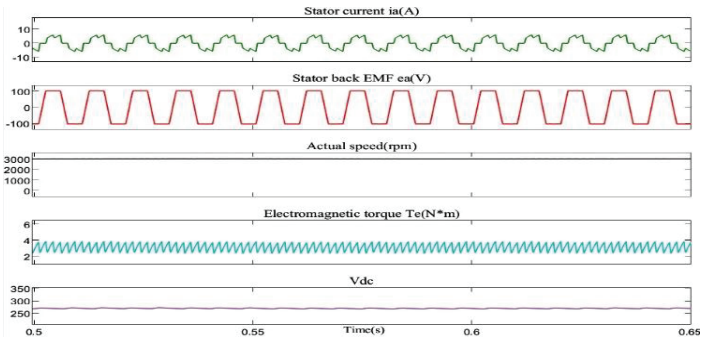

Fig 6. Steady State characteristics of BLDC Motor

b) Only Utility Grid Powering the BLDC Motor Pump

Since the system is solely powered by the utility grid, the PV array is inactive, as irradiance, voltage, current, and power remain constant and near zero. As depicted in (fig 7.), the system draws a sinusoidal supply current of 8.3 A (rms) from the grid, perfectly in-phase to guarantee efficient power transfer. Concurrently, the DC bus voltage is regulated at a stable 270 V, providing a reliable power supply to the motor.

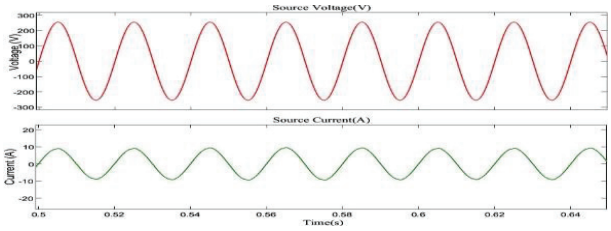

Fig 7. Steady State characteristics of Utility Grid

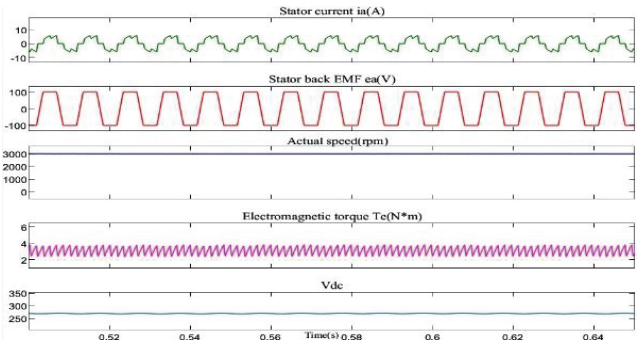

Fig 8. Steady State characteristics of BLDC Motor

c) When Water Pumping is not Necessary

As shown in Fig. 9, the Photovoltaic array operates at its maximum power point (MPP) condition under 1000 W/m² solar irradiation, optimizing energy harvesting. The presence of a phase shifted sinusoidal supply current signifies a reversal in power flow, where the surplus energy produced by the PV array is seamlessly injected back into the grid (fig 10).

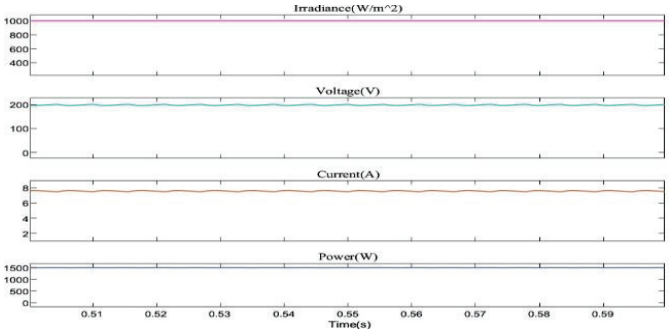

Fig 9. Steady State characteristics of PV Array

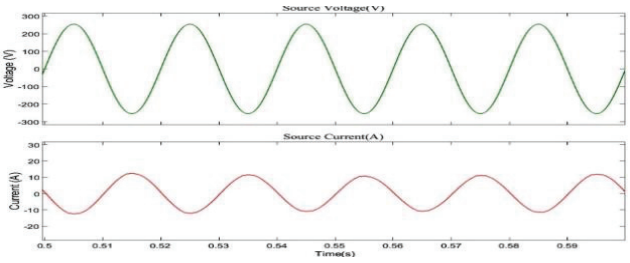

Fig10. Steady State characteristics of Utility Grid

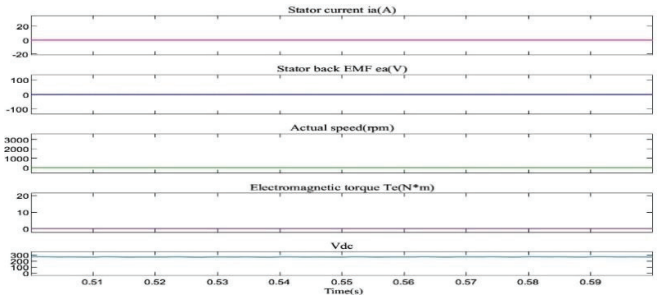

Fig 11. Steady State characteristics of BLDC Motor

B. Dynamic Characteristics

a) Transition from PV-Only pump operation to combined Grid and PV Power Supply

At first, the PV array provides enough energy to operate the water pump at full capacity. However, after 1 second, the solar radiation drops from 1000 W/m² to 300 W/m² (fig 12.). Before 1 second, the utility grid does not contribute power, as indicated by the zero supply current. After 1 second, the utility grid supplies the additional power needed, resulting in an in-phase supply current of 4.3 A (rms) as depicted in (fig 13).

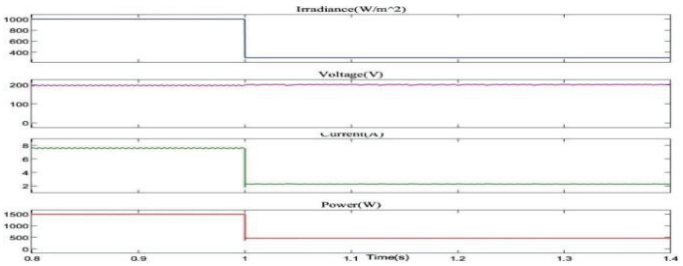

Fig 12. Dynamic characteristics of PV Array

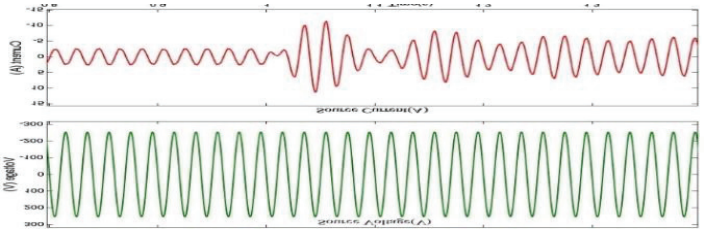

Fig 13. Dynamic characteristics of Utility Grid

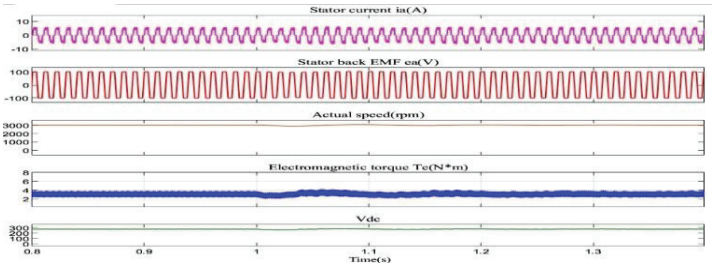

Fig 14. Dynamic characteristics of BLDC Motor

VII. DYNAMIC QUALITY ASPECTS

The proposed system adheres to IEEE 519 standards, thereby the total Harmonic Distortion (THD) of less than 5% is maintained in both cases (fig 15. And fig 16.).

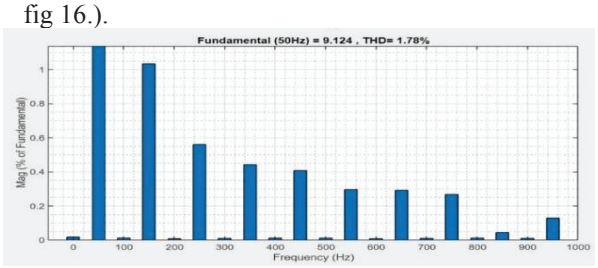

Fig 15. Harmonic Spectrum and THD of Supply Current when Water Pump is operated exclusively on the Utility Grid Power.

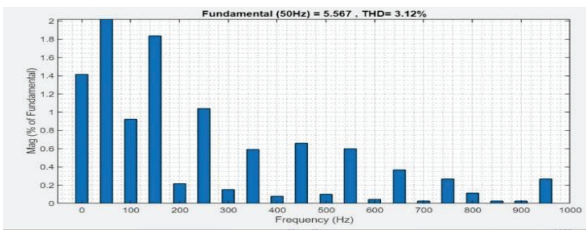

Fig 16 Harmonic Spectrum and THD of Supply Current with water pump powered by both Utility Grid and PV Array.

VIII. TORQUE RIPPLE ANALYSIS

i. Using conventional method

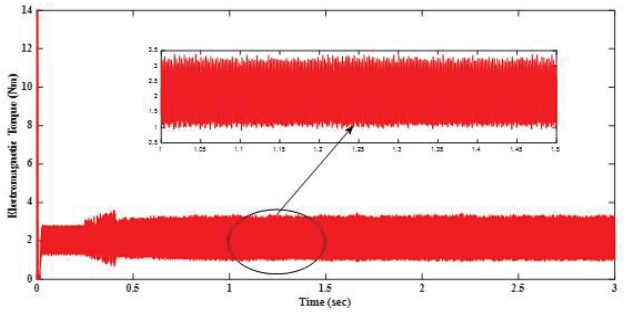

Fig 17. Torque ripple analysis using Hall-effect sensors

A load torque equivalent to 3Nm was exerted for a duration of 3 seconds.

Torque Ripple (%) $= \frac{T_{max}-T_{min}}{T_{max}} * 100 = \frac{3.25-1.2}{3.25} * 100 =$ 63.07%.

This means that the actual torque produced by the motor deviating from the desired torque by as much as 63.07%.

ii. By the implementation of PWM-ON-PWM switching scheme

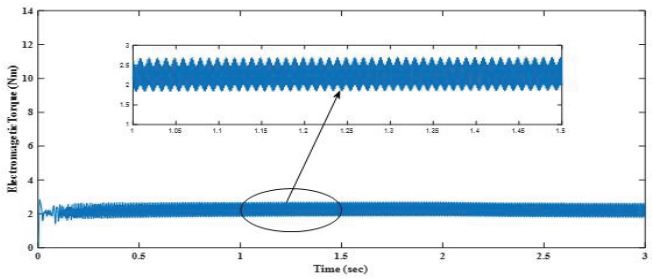

Fig 18. Torque ripple analysis using PWM-ON-PWM switching scheme.

A load torque equivalent to 3Nm was exerted for a duration of 3 seconds.

Torque Ripple (%) $= \frac{T_{max}-T_{min}}{T_{max}} * 100 = \frac{2.6-2.1}{2.6} * 100 =$ 19.2 %

The new PWM_ON_PWM method has greatly improved the performance of the BLDC motor. Torque ripples, which can cause vibrations and noise, have been reduced by 43.87% to just 19.2% compared to the scenario where only Hall-effect sensors are employed.

IX. CONCLUSION

The designed water pumping system integrates a solar PV array, a boost converter, a voltage source inverter, a BLDC motor, and a grid connection. The solar PV array generates power from sunlight, which is then converted to a stable DC voltage using the boost converter. The voltage source inverter converts the DC voltage to a three-phase AC voltage, which is fed to the BLDC motor. The motor drives a water pump, supplying water to agricultural or industrial applications. To ensure continuous operation, the system operates in conjunction with the grid, enabling a UVT based bidirectional power flow transfer. During periods of sufficient solar irradiance, the system operates in solar-only mode, utilizing the solar energy to power the motor. When the solar irradiance is insufficient, the system seamlessly transitions to grid-only mode, drawing power from the grid to ensure uninterrupted operation. Furthermore, during periods of excess solar energy generation, the system feeds surplus power back into the grid, maximizing energy utilization and economic feasibility. Utilization of PWM_ON_PWM switching technique alone resulted in an improved torque performance of the BLDC motor up to 43.87% rather than following the normal conduction mode (Hall-effect sensors alone). Simulation results confirmed the system's reliability, with power quality maintained within the IEEE standards, total harmonic distortion (THD) below 5% and a power factor close to unity.

In conclusion, the proposed grid-tied solar PV-based water pumping system offers a sustainable and efficient solution for water pumping applications. By integrating a solar PV array, a boost converter, a voltage source inverter, a BLDC motor, and a grid connection, the system ensures continuous operation, maximizes energy utilization, and minimizes torque ripple. The system's high efficiency, reliability, and economic viability make it an attractive solution for agricultural and industrial water pumping applications. As the world continues to shift towards renewable energy sources, this system has the potential to play a significant role in promoting sustainable and efficient water pumping practices.

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Off- Grid Solar Atmospheric Water Harvesting: Water Security for Seafaring Fishermen

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***Abstract*— This study focuses on the development and evaluation of an off-grid solar-powered atmospheric water harvesting system designed to enhance water security for seafaring fishermen. The primary aim is to create a prototype capable of extracting clean water from the air using ultraviolet (UV) radiation and solar energy, ensuring a reliable source of safe drinking water for fishermen on small vessels. The prototype employs a photovoltaic setup to power the system, enabling efficient water harvesting and purification through solar energy. This innovative solution addresses the critical need for freshwater accessibility in maritime environments, particularly benefiting fishermen who face challenges in obtaining potable water while at sea. The successful construction and assessment of this prototype demonstrate its potential to improve the quality of life and safety for seafaring communities.**

Keywords—Atmospheric water harvesting, Seafaring fishermen, Solar-powered

I. INTRODUCTION

Access to clean drinking water continues to be a major issue in many parts of the world, particularly in remote and off-grid areas where conventional water supply infrastructure is either insufficient or absent[1]. In these areas, communities often rely on unsafe water sources, leading to health problems and waterborne diseases. Furthermore, the lack of reliable energy sources exacerbates the situation, making it even more difficult to provide safe water. Solar off-grid atmospheric water harvesting (AWH) systems offer a promising and sustainable solution to these challenges. These systems are capable of collecting moisture from the ambient air and converting it into clean, drinkable water, offering a viable alternative to traditional water-sourcing methods in areas without access to piped water or grid electricity[2]. By utilizing solar energy, which is renewable and abundant in many regions, these systems not only provide access to potable water but also tackle the issue of energy access, making them a powerful tool in promoting sustainable development.

The technology behind atmospheric water harvesting is based on the principle of condensation[3]. The process typically involves using an evaporator coil, which cools the humid air drawn into the system[4]. As the air passes over the cooling coil, its temperature drops, causing the water vapor to condense into liquid form. This condensation process is similar to what happens when warm air comes into contact with a cold surface, causing moisture to form[5]. In the case of the AWH system, the condensed water collects on the surface of the coil and drips into a container where it is stored for later use[6]. The effectiveness of this system depends on the humidity levels and temperature of the air, but with the integration of energy-efficient cooling technologies, it becomes a reliable method for obtaining clean water in areas where other sources are not available[7]. This method of water harvesting is particularly suited for areas that experience high levels of humidity, making it a practical solution in many coastal, tropical, or temperate regions.

What makes these systems even more sustainable is the integration of photovoltaic (solar) panels to power the entire atmospheric water harvesting process[8]. Photovoltaic solar energy is used to supply electricity to run the cooling unit, air filtration system, and other necessary components of the AWH system. By using solar energy, which is a clean and renewable resource, these systems eliminate the need for fossil fuels or other non-renewable energy sources, which often contribute to environmental pollution and climate change. The use of solar power ensures that the system operates efficiently in off-grid areas where conventional power supplies may be unavailable[9]. Additionally, solar-powered atmospheric water harvesting systems reduce the overall carbon footprint and help mitigate the environmental impacts associated with water extraction and purification from traditional sources[10]. The combination of solar energy with advanced condensation technology results in an innovative and environmentally friendly solution for producing potable water[11]. It is

especially beneficial for remote communities that face both water scarcity and energy access issues, providing them with a reliable and sustainable source of clean drinking water[12]. By improving access to safe water, these systems can play a key role in improving public health, enhancing the quality of life, and fostering economic development in off-grid region.

The main objective of this paper is to design and develop an affordable, off-grid solar-powered atmospheric water harvesting system to improve water security for seafaring fishermen. It investigates the system's potential across diverse maritime environments, with the goal of providing sustainable and eco-friendly solutions for obtaining safe drinking water.

This paper is structured into six sections. Section I introduces the challenges of obtaining fresh water, explores sustainable options, and discusses the applicability of the atmospheric water harvesting (AWH) system. Section II provides an overview of the control block diagram for the proposed system. Section III analyses meteorological data collected from the India Meteorological Department for this study. Section IV details the experimental setup and components used. Section V presents the test results obtained from the system, specifically focusing on the quality of the harvested water. Finally, Section VI concludes the study.

II. System Overview

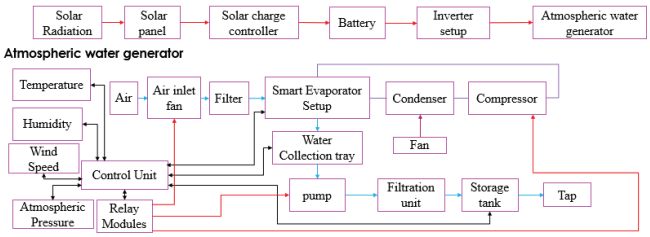

Fig. 1. Block Diagram of Proposed System

Our prototype consists of three main components: the water collection and purification system, the control system, and the power supply system.

The water collection and purification system utilizes a fan that draws in air. Warm air is drawn over the evaporator coils by a fan. The refrigerant inside the coils is at a lower temperature and pressure, allowing it to absorb heat from the air. As the refrigerant absorbs heat, it evaporates from a liquid to a gas. This phase change of the refrigerant extracts heat from the surrounding air, lowering its temperature.

As the air meets the cold evaporator coil, its temperature drops below the dew point (the temperature at which air can no longer hold moisture). This causes the water vapor in the air to condense into liquid droplets on the coil surface. The condensed water droplets accumulate and flow into a collection tray or reservoir. This water is collected in a 55-liter stainless steel tank. A diaphragm pump pushes the water through several stages of filtration: a 5-micron sediment filter, a Carbon Block/granular filter, an alkaline filter, and a final UV-C light treatment (254 nm). The cleaned water is stored in a bladder-type tank, which is connected to a dispenser.

The energy supply system consists of a photovoltaic panel, a charge controller, and a lithium-ion battery, providing up to 8 hours of autonomy without needing external power. The control system manages the operation of the prototype, overseeing three phases: shutdown, water collection (extraction of water from the air), and water purification.

A versions of the prototype were tested, with power ratings of 120 W. The prototype was placed on a boat, with the photovoltaic panels positioned on the deck to harness solar energy.

A. Smart evaporator setup

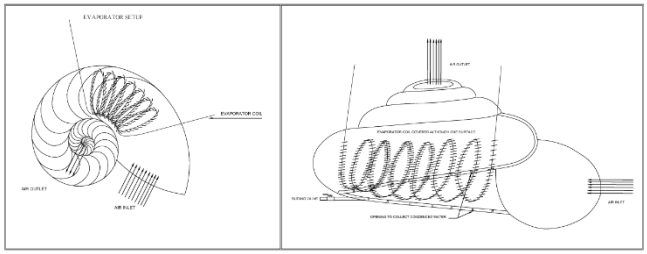

Fig. 2. Snail shell evaporator with spike in the interior walls

A snail shell model evaporator for atmospheric water generation can enhance the heat exchange process, maximizing efficiency in water condensation while minimizing energy consumption. This design mimics the spiral structure found in nature, which is often optimized for space efficiency and gradual, controlled airflow. By applying this geometry to an evaporator, it is possible to create a system that promotes efficient heat dissipation and maximizes contact between warm, humid air and cooler surfaces, where condensation occurs.
The evaporator is arranged in a spiral (snail shell) shape, allowing air to flow through the spiral path. As air travels along this path, it gradually cools, encouraging moisture in the air to condense along the evaporator's surface. This increases the overall surface area for condensation without taking up excessive space. This setup with spikes inside the evaporator walls is an innovative design that can improve efficiency in atmospheric water harvesting (AWH) systems. Spikes increase the total condensing area, allowing for more water droplet formation. The pointed spikes encourage faster droplet nucleation and prevent water from forming a continuous film that reduces efficiency. The shape of the spikes helps water droplets quickly detach and flow down to a collection system, reducing the chance of re-evaporation. Coating the spikes with a hydrophobic layer (e.g., graphene, PTFE) can enhance water droplet movement and collection efficiency. The combination of spiral airflow and spiked condensation surface ensures maximum moisture extraction.

By introducing humid air near the spikes, the system ensures that the localized temperature remains at or below the dew point, preventing heat buildup that could reduce condensation efficiency. The spikes provide an increased surface area and act as nucleation sites for water droplets. With the humid air consistently delivered nearby, droplets form more readily and efficiently, maximizing water collection. The tiny openings create localized microturbulence. This not only ensures even distribution of humid air but also improves the contact between water vapor and the cool surfaces, further aiding condensation. By maintaining optimal condensation

conditions, the system requires less energy to cool the evaporator below the dew point, reducing overall power consumption and enhancing the sustainability of the setup.

B. Various Sensors

Humidity Sensors: They measure the moisture content of the incoming air. This data helps in determining the dew point and adjusting the humid air injection accordingly.

Dew Point Sensors (or Calculated Dew Point): Often derived from temperature and humidity data, these sensors ensure that the evaporator maintains conditions favourable for condensation.

Pressure Sensors: Used to monitor the pressure of the pumped air, these sensors ensure that the tiny openings near the spikes are delivering air at the correct rate and distribution, preventing pressure drop or blockage.

Flow Sensors: These verify that the air is being evenly and effectively distributed throughout the evaporator, which is important for maintaining a uniform temperature profile and efficient condensation.

Water Level Sensors: To track the amount of water collected and manage the drainage system, water level sensors provide feedback for system performance and maintenance.

Together, these sensors form a feedback loop that allows the control system to adjust pump speeds, airflow distribution, and other operational parameters in real time, ensuring the evaporator remains at an optimal dew temperature and maximizing the overall efficiency of the system.

C. Control Unit

The control unit in an atmospheric water harvesting system serves as the brain of the operation. It collects data from all integrated sensors and processes it to ensure that the system operates at peak efficiency. It continuously gathers real-time data from various sensors, including temperature, humidity, dew point, pressure, and flow sensors. This detailed data provides a comprehensive picture of the system's operating conditions. Using built-in algorithms (often employing PID control or more advanced IoT-based software), the control unit analyses sensor inputs to determine if adjustments are needed. For example, it might detect if the evaporator surface is warming above the dew point and then trigger corrective actions. Based on the analysis, the control unit sends commands to adjust operational parameters such as pump speeds, air flow rates, or valve positions to maintain optimal conditions. This helps preserve the dew temperature, enhancing condensation efficiency. The control unit operates in a continuous feedback loop, constantly updating its commands as new sensor data is received. This ensures that the system adapts dynamically to changing environmental conditions without manual intervention. Often built on microcontrollers (like Arduino, Raspberry Pi) or PLCs, modern control units may also incorporate IoT capabilities. This allows for remote monitoring, data logging, and even cloud-based analytics for predictive maintenance and further efficiency improvements. By effectively managing the sensor data and adjusting the system parameters in real time, the control unit plays a critical role in maximizing water harvesting efficiency while reducing energy consumption.

D. Solar PV System

A solar inverter setup for an atmospheric water generator is essential for powering the system, especially in remote or off-grid locations and ensuring that the energy harvested from solar panels is effectively converted and used.

- **Solar Panels & Energy Collection**

Photovoltaic Modules: Solar panels capture sunlight and convert it into direct current (DC). For optimal performance, panels should be oriented to maximize sun exposure throughout the day.
Maximum Power Point Tracking (MPPT): MPPT technology in charge controllers optimizes the energy harvest by continually adjusting the electrical load to ensure the panels operate at their maximum power output.

- **Charge Controller & Battery Bank**

Charge Controller: The controller regulates the DC output from the solar panels, preventing overcharging of the batteries while ensuring a steady flow of energy.
Battery Storage: Batteries store excess energy, allowing the system to run during low-sunlight periods or at night. The battery bank must be sized based on the overall energy demand of the water generator and associated control systems.

- **Inverter Conversion**

DC-to-AC Conversion: The solar inverter converts the stored DC energy into alternating current (AC), which is typically required by the pumps, fans, sensors, and control units of the atmospheric water generator.

- **System Integration & Monitoring**

Control Unit Integration: The inverter setup is integrated with the system's control unit, which collects data from sensors (temperature, humidity, flow, etc.) and adjusts operations in real time for optimal water harvesting.
Remote Monitoring & IoT: Modern inverters often include features for remote monitoring, allowing system performance to be tracked, and maintenance issues to be detected early.
Safety & Surge Protection: Proper wiring, grounding, and surge protection are crucial to protect both the inverter and the atmospheric water generator from electrical faults and power surges.

A solar inverter setup provides a sustainable and renewable power source, reducing reliance on external grid power. Once installed, the system can operate with minimal ongoing energy costs, enhancing the economic viability of atmospheric water generation. The modular nature of solar panels and inverters allows the system to be scaled up or down based on water production requirements and available sunlight. Integrating a solar inverter into an atmospheric

water generator not only promotes sustainability but also ensures that the system has a reliable and consistent power supply, critical for maintaining the delicate balance of temperature and humidity needed for efficient water harvesting.

III. Meteorological Data Analysis

Meteorological data for this study were collected from the India Meteorological Department's Data Supply Portal (IMD-DSP Pune), which provides comprehensive observations including station level pressure, mean sea level pressure, dry and wet bulb temperatures, dew point, relative humidity, vapor pressure, and wind speed. Data was accessed on 14-02-2025. Among which a period of data is considered for the modeling of graphical representation. Which determines the efficient modelling of the atmospheric water harvesting unit.

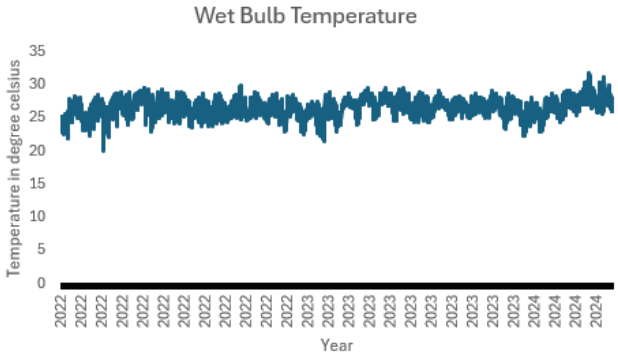

Fig. 3. Wet bulb temperature versus year representation

The wet bulb temperature is measured using a thermometer covered by a water-soaked cloth. As water evaporates from the cloth, it cools the thermometer. The final reading reflects both temperature and moisture in the air. A higher wet bulb temperature indicates moist, humid air, which is easier to condense. When the wet bulb temperature is close to the dry bulb (ambient) temperature, the air is nearly saturated, so very little additional cooling is needed for condensation. The graph indicates values between 20°C and 30°C, with minimal fluctuations. A higher wet bulb temperature (~25°C-30°C) ensures effective condensation in AWGs. Lower values (~20°C) indicate drier conditions, reducing the efficiency of water condensation

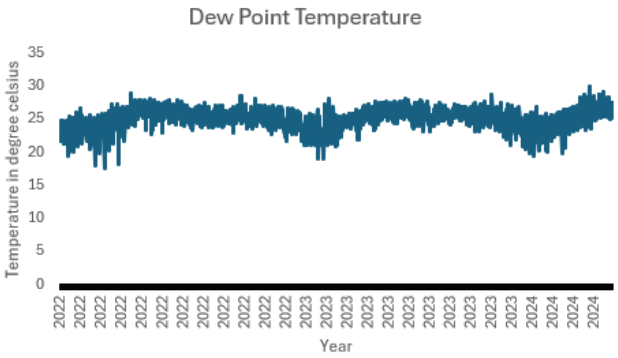

Fig. 4. Dew point temperature versus year representation

The dew point is the temperature at which air becomes fully saturated (100% RH), and water vapor begins to condense into liquid. A higher dew point means the air needs less cooling to reach saturation. For AWH, if the dew point is already relatively high (e.g., above 20°C), the system requires less energy to cool the air below that temperature and start condensation. The graph shows dew point values between 15°C and 30°C, with seasonal trends. Higher dew points (above 20°C) improve AWG efficiency, as air moisture is more easily condensed. A drop below 15°C makes condensation difficult, requiring additional cooling.

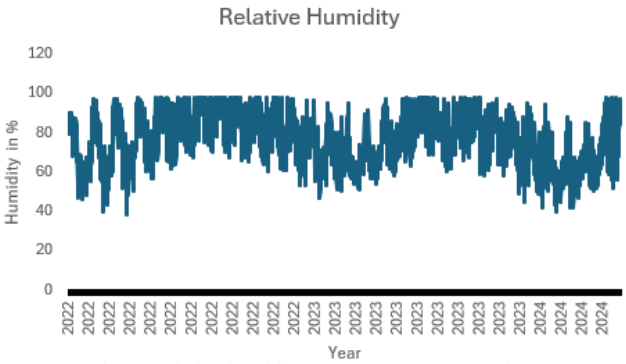

Fig. 5. Relative humidity versus year representation

Relative humidity is the percentage of moisture in the air compared to the maximum amount of moisture the air can hold at that temperature. Higher RH indicates that the air is closer to saturation, so less cooling is needed to reach the dew point (where condensation begins). Lower RH means the air can hold more moisture before reaching saturation, so an AWH system must cool the air more (or use more energy) to condense water. The graph shows humidity variations between 40% and 100%, with frequent fluctuations. Humidity >70% significantly enhances AWG efficiency, as air contains more water vapor. Drops below 50% indicate challenging conditions where water production is minimal.

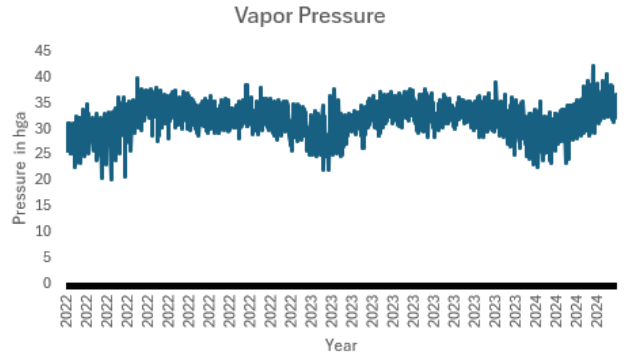

Fig. 6. Vapor pressure versus year representation

Vapor pressure is the partial pressure exerted by water vapor in the air. A higher vapor pressure means there is more water vapor present. In AWH systems, more water vapor in the air makes it easier to condense because the air is already holding a significant amount of moisture. The graph shows vapor pressure fluctuating between 20-40 hga, with seasonal variations. Higher values (above 30 hga) are ideal for efficient AWG performance. Low-pressure periods (<25 hga)

indicate reduced moisture content, lowering condensation rates.

The reason these factors are so critical is that they collectively determine the moisture content in the air and the energy required to cool that air to its condensation point. By targeting higher ranges for vapor pressure, relative humidity, dew point, and wet bulb temperature, an Atmospheric Water Generator can maximize water production while minimizing energy consumption, leading to efficient water harvesting.

TABLE I. FIELD DATA COLLECTED

Sl. No.	Temperature	Humidity	Time
1	33.1^{0}C	61%	3:20pm
2	35.2^{0}C	57%	3:23pm
3	31.8^{0}C	66%	3:26pm
4	30.6^{0}C	73%	3:33pm
5	32.5^{0}C	61%	3:42pm
6	32.4^{0}C	60%	3:45pm

IV. Experimental Setup and Components

This setup harnesses a vapor-compression refrigeration cycle to extract water from ambient air. By cooling the air below its dew point, water vapor condenses on surfaces, allowing collection of liquid water. In this experiment, the system is optimized to yield approximately 500 ml of water in 15 minutes.

The evaporator is enhanced with fins to maximize the surface area for heat transfer. As the refrigerant absorbs heat from ambient air in the evaporator, the temperature drops, causing the moisture in the air to condense on its surface. The compressor circulates refrigerant (R134a) through the system. It compresses the refrigerant vapor, increasing its pressure and temperature before it enters the condenser. R134a is used due to its favorable thermodynamic properties, facilitating an efficient phase-change process in the vapor compression cycle. After compression, the hot refrigerant passes through the condenser coil where it releases heat to the surroundings and condenses into a liquid. The larger surface area of the condenser aids in rapid heat rejection and effective condensation. A 1000 W inverter converts DC power from a solar panel (regulated by an appropriate charge controller) to AC, which powers the compressor and other electrical components. This renewable energy source makes the system viable even in off-grid conditions.

The compressor circulates R134a through the evaporator, where it absorbs heat from the ambient air. This cooling effect reduces the air temperature below its dew point, and moisture condenses on the finned surface of the evaporator. The low-pressure refrigerant vapor is compressed, raising its temperature and pressure. It then flows through the condenser coil where it loses heat, condensing into a high-pressure liquid before cycling back to the evaporator. The condensed water is collected from the cooled surfaces. The design and dimensions of the coils ensure that, under optimized conditions, about 500 ml of water is harvested in 15 minutes. Solar panels supply the DC power that, after conversion by the 1000 W inverter and regulation via the charge controller, drives the compressor reliably, ensuring that the system can operate sustainably off-grid.

Fig. 7. Experimental Setup

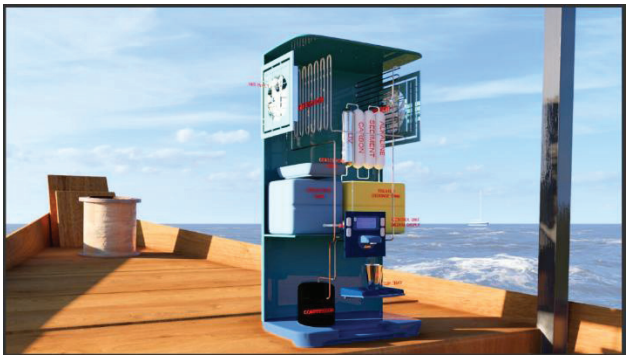

Fig. 8. 3D Model of Prototype

This experimental setup demonstrates an integrated approach to atmospheric water harvesting by combining a well-designed vapor compression cycle with renewable energy. The use of specifically sized evaporator and condenser coils, along with the selection of a 60 W compressor and R134a refrigerant, allows for efficient water extraction. Such systems are part of a broader trend in water harvesting research, similar in principle to other solar-powered atmospheric water harvesting devices explored in recent studies

TABLE II. COMPONETS AND SPECIFICATIONS

Sl. No.	Components	Power Rating	Range/ Dimensions
1	Solar Panel Array	18V, 2.27A	
2	Inverter Circuit	230V AC, 1000W	
3	Solar Charge Controller	30A,12/24V	
4	Battery	12/48V, 60Ah	
5	Evaporator		300mm*200mm
6	Condenser		450mm*200mm
7	Compressor	230V, 60W	
8	Blower Fan	12V, 4.3W	
9	Air Filter		300mm*200mm
10	Pt 100 (Temp Sensor)	3-10V, 1mA	-200^{0}C to 850^{0}C
11	RH Sensor (Humidity)	3-5V, 0.5-2mA	
12	Capacitor Sensor (Water Level)	10V, >20mA	
13	Arduino Mega	5V	

14	Relay Module	5/230V	
15	Storage Tank		250mm*200mm*180mm
16	Pump (mini)	12V	

V. Results and Discussion

An atmospheric water harvesting system using the condensation method captures water by cooling air below its dew point, resulting in condensation of water vapor. The volume of water collected depends on factors like humidity, temperature, and system efficiency, with higher humidity typically yielding more water. While the water is generally clean, it may need filtration or treatment due to potential environmental contaminants. The system requires energy, usually from electricity or solar power, to cool the air, making energy consumption a key factor in determining efficiency. Local weather conditions, such as temperature and humidity, significantly impact the system's performance, while external pollutants may affect both the quantity and quality of the collected water. System performance can be evaluated by comparing the amount of water harvested to the energy used or the area covered, which helps assess its overall sustainability and practicality.

VI. Conclusion

The development and evaluation of an off-grid solar-powered atmospheric water harvesting system have proven effective for seafaring fishermen. Using UV radiation and solar energy, the prototype efficiently extracts clean water from ambient humidity, ensuring safe drinking water on small vessels. The system's design includes evaporator coil condensation and multiple filtration systems, meeting quality standards for consumption. Powered by a photovoltaic setup, this eco-friendly and cost-effective solution addresses freshwater scarcity in maritime environments. The study confirms the system's ability to generate water that meets DIGESA standards, highlighting its potential to enhance the quality of life and safety for seafaring communities.

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Coast-Cleaner Bot (CC-BOT)

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***Abstract*—The work proposes the design process of making a Coast Cleaner robot which address the critical issue of beach pollution. The paper focus on creating an environmentally friendly solution for cleaning beaches by collecting wastes such as plastics, needles, glass and other debris. The bot is equipped with a mechanical waste collection system and real time video streaming for remote operation and monitoring. Unlike conventional beach cleaning methods, the bot enhances operational flexibility, ensuring efficient cleaning while reducing manual labor and human intervention in challenging environment.**

Keywords—Coast Cleaner Robot, Real Time Video Streaming

I. Introduction

CC-BOT is a remote-controlled beach cleaning robot intended to clean up coastal areas. Coastal pollution has become a significant environmental concern, with the accumulation of waste materials on beaches on an alarming rate. Polluted beaches affect marine ecosystem as sea creatures may ingest or entangles themselves in waste, leading to fatal consequences. Besides beach pollution affect tourism, local economies and public health. While conventional beach cleaning techniques rely heavily on human labor and large-scale machinery, the coast clean bot is developed as a technology advanced cost-effective solution for beach cleaning. The bot is designed to effectively collect surface waste ensuring cleaner shorelines while reducing human efforts and operational expenses.

The CC-BOT is equipped with a mechanical waste collection system and real time monitoring system for remote operation and monitoring. The monitoring system is equipped with ESP32-CAM for navigating beaches by detecting wastes and avoiding obstacles. While the mechanical waste collection system has the rake positioned at the front which direct the sand and debris to the mesh conveyer belt for separation. The toothed conveyer belt prevents the collected waste from slipping out and it is made of a mesh like structure to further remove any sand particles that would have got through. There will be a storage compartment to store wastes and pressure sensors to detect the amount that is being filled. A single integrated module is utilized for both driving and cleaning functions. This paper provides a comprehensive analysis of cc-bot's design, working mechanism and its advantages in the automated waste collection. By implementing modern technology into coastal cleaning, CC-BOT contribute to sustainable waste management practices by helping to preserve marine biodiversity and ecological wellbeing of beaches worldwide.

II. Literature Survey

Recent advancements in robotics have led to innovative solutions for beach cleaning. Denny Varghese and Ashish Mohan (2022) introduced Binman, an autonomous beach-cleaning robot designed for efficient waste collection. Their study highlights how automation can improve coastal cleanliness by reducing manual labor and increasing operational efficiency. Similarly, Arafa Omer Qasim et al. (2022) developed Clean-B, a modular beach-cleaning robot designed for adaptability in different environments. By focusing on modularity, their approach allows for better scalability and customization based on varying beach conditions. Both studies emphasize the growing role of robotics in environmental sustainability.

In addition to automation in beach cleaning, remote driving technology has seen significant progress. Yang Yu and Sanghwan Lee explored remote driving control with real-time video streaming over wireless networks, focusing on low-latency and high-reliability communication. Their research provides insights into optimizing wireless networks for seamless control, ensuring smooth and responsive operations. These advancements in remote control technology have applications beyond autonomous vehicles, including robotic systems designed for hazardous or inaccessible environments.

The integration of autonomous and remotely controlled technologies can further enhance robotic applications, including beach-cleaning robots. By incorporating real-time video streaming and remote-control capabilities, these robots could become more efficient, adaptable, and user-friendly. The combination of automation and remote operation opens new possibilities for large-scale environmental management, highlighting the importance of continued research and innovation in these fields.

III. MATHEMATICAL ANALYSIS

1) Weight Distribution.

The total mass of the CC-BOT includes the robot's body and the collected waste. The relation can be expressed as:

$$M_{total} = M_{bot} + M_{waste} \quad \text{-----(1)}$$

$M_{total} = 11$ kg

$M_{waste} = 2.5$ kg

Thus, the robot's body mass is:

$M_{bot} = 11\text{-}2.5 = 8.5$ kg

2) Motor Torque Estimation.

The CC-BOT is powered by four 12V motors, which must generate sufficient torque to move the robot across sandy terrain.

The force required to move the bot depends on rolling resistance:

$$F = M_{total} * g * \mu \quad \text{-----(2)}$$

$g = 9.81$ m/s^2

$\mu = 0.02$

Substituting values:

$F = (11*9.81)*0.02 = 2.16$ N

Since the bot uses four motors, the torque per motor is calculated as:

$$T_{motor} = (F*r)/4 \quad \text{-----(3)}$$

$T_{motor} = (2.16*0.05)/4 = 0.027$ Nm

Each motor must provide a minimum torque of 0.027 Nm to ensure smooth movement.

3) Power Consumption Analysis.

The power required by each motor is given by:

$$P = V * I \quad \text{---(4)}$$

$P_{motor} = 12*2 = 24$ W

$P_{total} = 4*24 = 96$ W

Considering a 12V, 7Ah battery, the total current drawn is:

$I_{total} = P_{total / V} = 96/12 = 8$A

The estimated battery runtime:

Runtime = Battery Capacity / I_{total} = 7/8 =0.88 hours = 52 minutes.

IV. MECHANISM OF CC-BOT

The CC-BOT is a specialized beach cleaning robot designed to collect waste efficiently while minimizing environmental disturbances. Its mechanism integrates a single module for both driving and cleaning, ensuring a compact and efficient system. The robot's design incorporates multiple subsystems, including the driving mechanism, cleaning mechanism, waste collection system, remote control system, and power management system, all working in synchronization to achieve effective beach-cleaning operations.

A. Driving Mechanism

CC-BOT employs a four-wheel drive system powered by four individual 12V DC motors, providing enhanced mobility over sandy terrain. The L298N motor drivers are used to control motor speed and direction, allowing precise maneuverability. The robot utilizes differential speed control to facilitate steering, adjusting the speed of individual motors instead of relying on a separate steering mechanism. By integrating the driving and cleaning mechanisms into a single module, CC-BOT maximizes space efficiency and ensures seamless operation. This design choice enables simultaneous motion and cleaning, making the system more effective in collecting waste while moving across the beach.

B. Cleaning Mechanism

The cleaning system consists of a rake and a toothed conveyor belt, which work together to extract waste while filtering out excess sand. Positioned at the front of the robot, the rake guides sand and debris onto the conveyor belt, ensuring that the collected waste is efficiently funneled into the system. The conveyor belt is designed with a mesh-like structure, allowing fine sand particles to pass through while retaining solid waste materials such as plastic, metal, and other debris. The toothed design of the conveyor belt prevents the collected waste from slipping back onto the beach, ensuring effective transfer to the storage compartment. The continuous movement of the conveyor facilitates uninterrupted cleaning, allowing the robot to operate efficiently over large areas.

C. Waste Collection System

Once the waste is separated from the sand, it is directed to a storage compartment located at the rear of the robot. The storage unit is designed to accommodate different types of waste and prevent spillage during movement. To optimize waste management, pressure sensors are integrated into the compartment to monitor the fill level. These sensors provide real-time feedback on the amount of collected waste, allowing users to determine when the storage compartment needs to be emptied. This automated monitoring system ensures efficient waste disposal and prevents overflow, improving the overall effectiveness of CC-BOT in long- duration cleaning tasks.

D. Remote Control System

CC-BOT operates via a Wi-Fi-based remote control system, allowing users to monitor and control its functions from a distance. A web-based interface, accessible through a local IP address, provides a user-friendly platform for controlling the robot's movement, activating the cleaning mechanism, and monitoring operational parameters. The robot is also equipped with an ESP32-CAM module, which provides real-time video feedback to the operator. This live camera feed enhances control precision, especially in areas with dense waste accumulation. Additionally, the system transmits real-time updates on critical parameters such as conveyor belt movement, steering adjustments, and waste collection status. This connectivity feature ensures that users can efficiently operate CC-BOT with minimal manual intervention.

E. Power System

CC-BOT is powered by a 12V lithium-ion battery, which supplies energy to all electronic and mechanical components while simultaneously acting as a counterweight for stability. To enhance energy sustainability, the robot is equipped with

a portable solar charging station, allowing on-site recharging without reliance on external power sources. The 20W solar power system is implemented to provide continuous energy replenishment, making CC-BOT an eco-friendly and self-sustaining cleaning solution. The combination of battery power and solar energy extends the robot's operational time, enabling it to cover larger beach areas without frequent recharging.

In designing CC-BOT, environmental sustainability and safety have been key considerations. The robot is constructed using lightweight and eco-friendly materials to minimize its environmental impact. Low-noise motors ensure that CC-BOT operates with minimal disturbance to beach wildlife and visitors. Additionally, failsafe mechanisms such as emergency stop functions are incorporated to prevent accidents and ensure safe operation in public spaces. These design features make CC-BOT a reliable and environmentally responsible solution for automated beach cleaning.

Fig.1. Representation of Mesh screen of CC-BOT

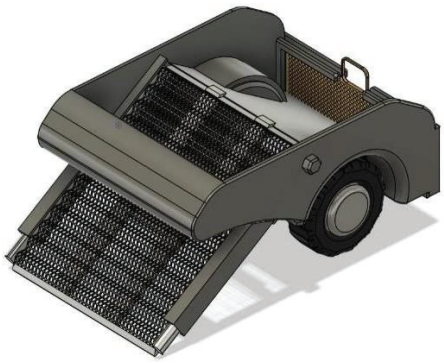

Fig.2. Representation of the rear module of CC-BOT

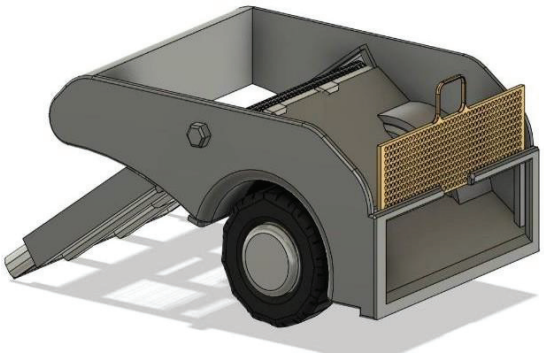

Fig.3. Removable Mesh screen of CC-BOT

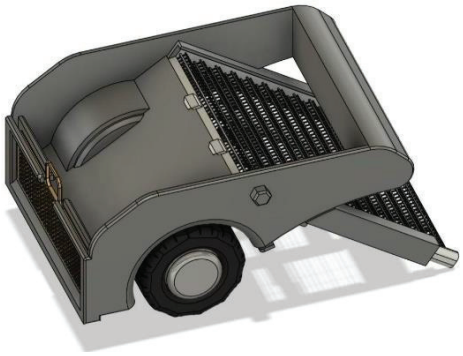

Fig.4. Top-View of waste storage compartment.

V. CIRCUIT DIAGRAM OF CC-BOT

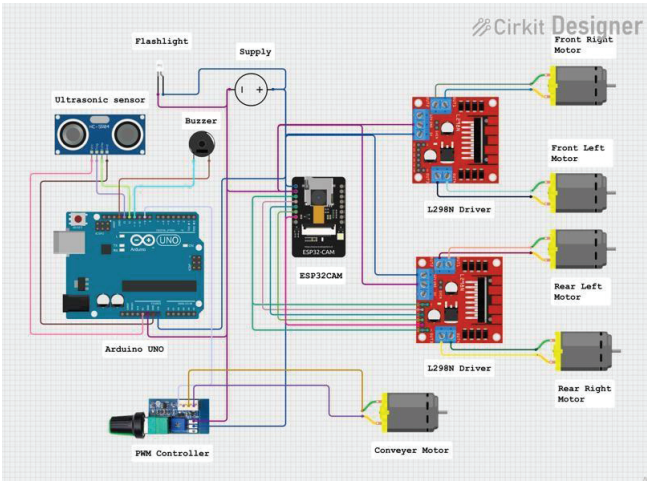

Fig.5. Circuit diagram of driving and video feedback

The circuit diagram of CC-BOT represents an integrated system designed for efficient beach cleaning. At its core, the ESP32CAM acts as the primary microcontroller, processing data from the user and controlling the movement of the robot. The ESP32-CAM module is responsible for real-time video streaming, allowing remote monitoring and control. To detect waste filling, the ultrasonic sensor is used, sending distance measurements to the Arduino, which then alerts the user that the storage is full. Additionally, a buzzer is included to provide alerts, indicating the CC-BOT operational and waste storage status. A flashlight is also present to enhance visibility in low-light conditions.

For motion control, the robot is equipped with two L298N motor drivers, each managing two motors. One driver controls the front left and right motors, while the second driver operates the rear left and right motors, enabling precise movement in all directions. The conveyor motor, which is crucial for waste collection, is separately controlled via a PWM controller that regulates its speed. The integration of these components ensures that the robot can navigate the beach efficiently while simultaneously collecting debris.

A centralized power supply ensures all components receive the necessary voltage for proper operation. Various wired

connections facilitate communication between the microcontrollers, sensors, and actuators. The combination of real-time video feedback, obstacle detection, and motorized waste collection makes CC-BOT an intelligent and automated cleaning solution. With its ability to be remotely operated, it can efficiently clean large beach areas while minimizing human intervention.

Overall, the design not only focuses on automation but also ensures adaptability for different environments. The combination of real-time video streaming and sensor-based navigation allows users to remotely monitor and control the robot, making it a versatile tool for beach maintenance. The PWM-controlled conveyor motor ensures efficient waste collection by adjusting its speed based on the type and quantity of debris. This modular design also allows for potential upgrades, such as adding more sensors for improved obstacle detection or integrating AI-based image processing for better waste identification. By combining multiple technologies, CC-BOT provides an effective and eco-friendly solution for keeping beaches clean.

VI. RESULT

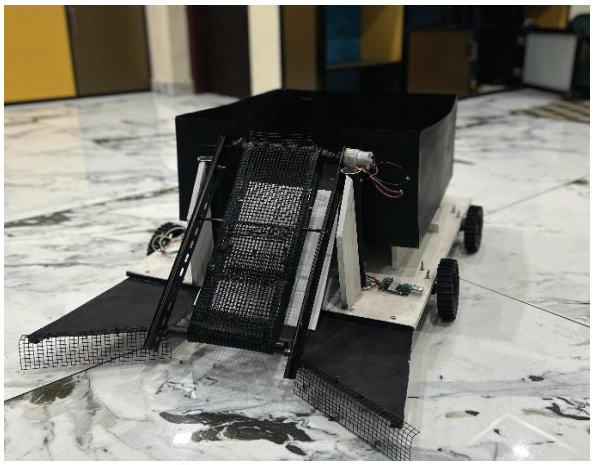

Fig 8.1. Front view of CC-BOT

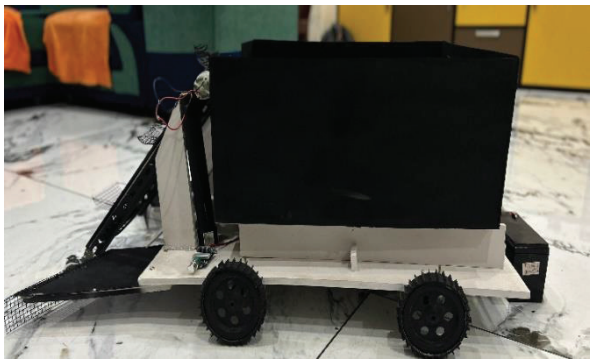

Fig 8.2 . Side View of CC-BOT

The CC-BOT successfully carried out its primary function of collecting waste from sandy surfaces, effectively filtering out debris while allowing sand to pass through. Its conveyor mechanism, driven by a DC motor, played a key role in transporting collected waste into the storage compartment. The addition of side panels and a mesh design significantly enhanced its ability to capture small plastic particles, bottle caps, and other litter that often get buried in the sand. The robot demonstrated stable movement across uneven terrain, ensuring smooth operation in real beach environments. Furthermore, its electronic control system functioned seamlessly, allowing for precise and efficient operation throughout the process.

The project's mechanical design and careful material selection contributed to the robot's durability and efficiency, minimizing operational disruptions. The successful implementation of CC-BOT validated the potential of robotic technology in beach cleaning, providing an innovative and efficient solution for environmental waste collection. By reducing reliance on manual labor and making the cleaning process more systematic, CC-BOT can play a significant role in maintaining cleaner beaches and promoting environmental sustainability.

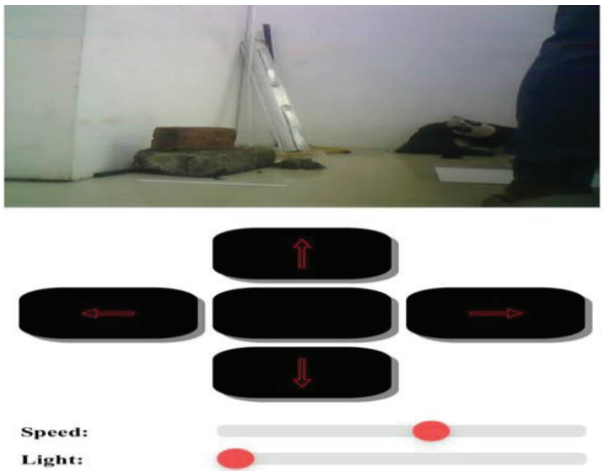

Fig 8.3 Web interface for User Control

The web-based user interface for remotely controlling the bot is designed to function within a local IP network, ensuring a stable and secure communication channel. This system allows users to operate the bot within an approximate range of 300 meters, with the option to extend coverage further using network extenders. A key benefit of this setup is that it facilitates remote operation while providing real-time video feedback, enabling users to effectively monitor the bot's surroundings.

A notable feature of the interface is its user-friendly directional control, which includes on-screen buttons for forward, backward, left, and right movements. Instead of relying on a traditional steering mechanism, the bot adjusts its direction by varying the speed of individual motors, a method known as differential speed control. This approach enhances maneuverability, allowing for precise navigation across various terrains and obstacles. Additionally, the interface includes adjustable sliders for both speed and lighting control. The speed slider enables users to regulate movement based on different operational needs, while the illumination control adjusts onboard lighting for improved visibility in low-light conditions or nighttime use.

Since the system operates over a local network, it remains independent of external internet connections, reducing latency and ensuring a responsive control experience. This local IP-based setup also enhances security by preventing unauthorized external access. Furthermore, integrating network extenders allows users to expand the operational range beyond 300 meters, making it suitable for covering larger areas without connectivity issues.

In summary, this remote-control system integrates real-time video streaming, precise movement control, adjustable speed

and lighting settings, and a secure local network connection to offer a seamless and efficient user experience. These features make it well-suited for applications requiring remote navigation, surveillance, or autonomous monitoring across various environments.

VII. Conclusion

The results of CC-BOT's implementation demonstrate its effectiveness in collecting waste from beach environments. The robot successfully identified and gathered various types of debris, showcasing its potential as a practical solution for beach cleaning. Its efficiency in navigating sandy terrain and collecting waste highlights the feasibility of using robotic systems for environmental conservation.

While the current version of CC-BOT performs well under controlled conditions, further enhancements are needed for large-scale deployment. Future improvements could include advanced image processing for better waste detection, enhanced mobility for different terrains, and increased operational efficiency. Integrating AI-driven decision-making and automation can further optimize its performance.

In conclusion, CC-BOT presents a promising approach to beach cleaning, combining technology and sustainability. The project demonstrates how robotics can contribute to environmental protection, paving the way for more advanced solutions in the future.

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Physiotherapy Assistant Device After Knee Replacement Surgery

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***Abstract*— Knee replacement surgery is a major procedure for individuals experiencing intense knee pain, requiring a well-structured recovery process to regain movement and strength. This paper explores the development and use of an electrical physiotherapy device designed to support knee replacement patients in their rehabilitation journey. The device is equipped with three stepper motors, each focusing on a different joint: the hip, knee, and ankle. It functions in four customizable modes, including a walking mode, allowing for a tailored recovery experience based on individual needs. A user-friendly mobile application connects with the device, giving patients the ability to adjust settings such as movement angles and repetition count. The findings indicate that this device can significantly aid the healing process, making rehabilitation more effective while also encouraging patients to stay actively involved in their exercises.**

Keywords—physiotherapy, Knee replacement, stepper motors, Arduino Mega 2560,

I. Introduction

Knee replacement surgery is a crucial medical procedure primarily performed on individuals suffering from degenerative joint diseases such as osteoarthritis and rheumatoid arthritis. These conditions lead to severe pain, stiffness, and reduced mobility, significantly impacting a person's quality of life. The primary goal of knee replacement surgery is to relieve this chronic discomfort, enhance joint function, and restore the patient's ability to perform daily activities with more ease. By replacing the damaged knee joint with an artificial implant, the procedure helps improve stability and movement, allowing individuals to regain their independence and also to improve the quality of life. Given the increasing prevalence of knee-related disorders, knee replacement surgery has become a widely adopted solution, offering long-term relief and improved functionality for patients struggling with persistent joint deterioration.

Effective post-operative rehabilitation plays a crucial role in helping patients regain strength and restore their range of motion after knee replacement surgery. Conventional physiotherapy techniques, while beneficial, often fall short in terms of personalization and sustained patient engagement, which can impact recovery outcomes. To address these limitations, this project presents a novel electrical physiotherapy device that offers customized rehabilitation exercises specifically designed for individuals recovering from knee replacement surgery. The device incorporates three stepper motors, each targeting a key joint—the hip, knee, and ankle—to facilitate controlled and progressive movement. By enabling adjustable therapy modes, this system ensures a more personalized rehabilitation experience, allowing patients to recover at their own pace while maintaining motivation and adherence to their therapy session.

The proposed device is powered by an Arduino microcontroller and features four unique operational modes: Warm-Up, Lift, Fold, and Walking. These modes are specifically designed to support different stages of the rehabilitation process, ensuring a structured and effective recovery. A key aspect of the system is its integration with a mobile application, which allows healthcare professionals to personalize therapy sessions according to each patient's specific requirements. Through the app, parameters such as movement range, speed, and repetition count can be modified, ensuring a tailored rehabilitation approach that adapts to the patient's progress. This level of customization enhances patient engagement and improves overall recovery outcomes.

II. METHODOLOGY

To develop an effective solution for post-operative knee rehabilitation, we initiated our research by conducting interviews with physiotherapists. This approach allowed us to gain firsthand insights into the challenges faced by both patients and medical professionals. To gather quantitative data, we designed and distributed a structured survey aimed at understanding the difficulties encountered during physiotherapy, patient concerns, and the effectiveness of existing rehabilitation methods. Based on the survey findings, we identified that the primary challenges for patients include pain around the surgical wound, muscle stiffness—especially in elderly patients—and difficulty accessing physiotherapy services due to mobility

constraints. Additionally, financial burdens and patient discomfort with opposite-gender physiotherapists were common concerns. Physiotherapists also reported challenges in assisting patients effectively, particularly when dealing with individuals with limited mobility.

The knee replacement surgery is of two types

- Total knee replacement
- Partial knee replacement
- Key hole surgery

Calcium depletion in bones leads to wear and tear, necessitating knee replacement surgery. After surgery, early post-operative exercises are essential for recovery. Pain points are mainly around the surgical wound, and elderly patients may experience muscle stiffness. Most patients are women over 40. Post-surgery, patients require 3-4 months of physiotherapy, costing ₹700 per hour, which is a financial burden. Some patients feel uncomfortable with physiotherapists of the opposite gender. Physiotherapists also face difficulties while assisting patients. Physiotherapy must be done in hospitals until discharge and continued as per prescribed schedules. Traveling to hospitals for physiotherapy is challenging for elderly patients.

From the data collected, we determined that three fundamental exercises play a crucial role in post-surgical knee rehabilitation:

The main exercises are

A. Straight leg raises

- To strengthen your thigh muscles and improve knee stability, start by fully straightening your knee while lying down.
- Engage your thigh muscles by tightening them and then lift your leg several inches off the surface.
- Hold this position for approximately 5 to 10 seconds before gradually lowering your leg back down.
- Repeat this movement until your thigh muscles become tired. Ideally, this exercise should be performed for about three minutes to maximize its effectiveness.

Additionally, you can perform a variation of this exercise while seated. Sit upright and engage your thigh muscles by tightening them. Keep your leg fully extended without any support beneath the knee. Maintain this position as before, holding for a few seconds before releasing. Continue repeating this exercise regularly to help rebuild muscle strength and enhance knee function. Consistent practice will aid in restoring full strength to your thigh over time.

B. Ankle pumps

To promote circulation and reduce swelling in your lower leg and ankle, perform a simple yet effective foot exercise.

- Begin by rhythmically moving your foot up and down, engaging both your calf and shin muscles. This movement helps stimulate blood flow, preventing stiffness and minimizing the risk of blood clots.
- For optimal results, practice this exercise for about 2 to 3 minutes at a time, repeating it 2 to 3 times every hour while in the recovery room. An easy way to incorporate this into your routine is by doing it during every commercial break while watching television.

Continue performing this movement regularly throughout your recovery period. Consistency is key—keeping up with this exercise will help alleviate swelling in your ankle and lower leg while also improving flexibility and overall mobility.

C. Bed-Supported knee bends

- To improve knee flexibility and strength, begin by slowly sliding your foot toward your buttocks while keeping your heel in contact with the bed.
- As your knee bends, aim to bring it into the deepest bend possible and hold this position for about 5 to 10 seconds. This stretch helps enhance joint mobility and range of motion.
- Once you have held the bent position, gradually straighten your leg back to its starting position.

Repeat this movement multiple times until you feel muscle fatigue or until you achieve a full knee bend. Ideally, this exercise should be performed for approximately two minutes to maximize its benefits.

Consistent practice will aid in restoring knee movement and improving overall joint function during recovery.

III. COMPONENTS AND SPECIFICATIONS

1.Microcontroller Board (Arduino Uno/Mega): Functions as the primary processing unit, interpreting signals from the mobile application and managing motor operations.

2. Precision Stepper Motors (NEMA 17): Three distinct motors facilitate different joint movements:

- Hip Actuator: Assists in raising and lowering the leg.
- Knee Actuator: Enables controlled flexion and extension of the knee.
- Ankle Actuator: Supports foot movement for enhanced mobility.

3. Motor Driver Modules (A4988): Regulate the stepper motors by adjusting electrical current and speed, ensuring smooth operation through microcontroller integration.

4. Wireless Communication Module (HC-05 Bluetooth): Establishes a seamless connection between the microcontroller and the mobile interface, allowing real-time adjustments.

5. Safety Limit Switches: Restrict motor movement beyond predefined angles to prevent mechanical strain and ensure user safety.

IV. SYSTEM OPERATION AND FUNCTIONALITY

The rehabilitation system functions through a continuous loop that actively monitors incoming signals from the mobile application. When a user selects a specific mode or modifies

the therapy parameters, the mobile app transmits the data via Bluetooth to the microcontroller, which then interprets and executes the corresponding command.

1. Mode Selection

Patients can choose from four distinct therapy modes, each targeting specific joint movements:

- Warm-Up Mode: This mode focuses on foot mobility, where the ankle motor gradually rotates up to 80 degrees to facilitate stretching and improve flexibility.
- Leg Lift Mode: The hip actuator raises the leg to a maximum of 90 degrees, promoting muscle engagement and enhancing range of motion.
- Knee Flexion Mode: The knee motor bends the joint to a maximum of 90 degrees before returning to its original position, aiding in knee strengthening and mobility.
- Walking Assistance Mode: This mode replicates natural walking movements by coordinating the hip motor to move the leg forward and backward within a controlled range of up to 30 degrees, simulating a walking motion.

2. Motion Execution and Control

The system ensures precise motor control by transmitting commands to the corresponding motor driver, which dictates the position, speed, and acceleration of each movement.

The Accel Stepper library is utilized for smooth and controlled motor operation, ensuring gradual acceleration and deceleration to prevent sudden jerks or strain on the joints.

Limit switches serve as protective mechanisms, continuously monitoring motor position. If a motor reaches its designated limit, the switch halts further movement to prevent over-rotation and potential mechanical damage.

3. Real-Time Adjustments and Feedback

The mobile application provides an interactive interface where users can modify movement parameters, such as adjusting the maximum bending angle and repetition count, allowing for a customized therapy experience.

Real-time feedback ensures that users and medical professionals can monitor session progress, enabling timely adjustments based on patient needs.

4. User Interface and Interaction

The mobile app communicates with the microcontroller using simple command structures. For example, sending a command labeled “Mode 1” triggers the warm-up exercise, while other modes can be activated similarly.

The app displays real-time data on motor activity, ensuring users stay informed about their therapy progress.

By integrating a user-friendly control system, patients can easily manage their rehabilitation routine, making therapy sessions more engaging and effective.

This structured approach ensures a safe, adjustable, and efficient rehabilitation process, helping patients regain mobility with enhanced comfort and control.

V. CONCLUSION

The development of this electrical physiotherapy device offers a significant advancement in knee replacement rehabilitation by providing targeted support for key joints involved in movement. With its customizable modes and user-friendly mobile application, patients can actively participate in their recovery process, ensuring a more personalized and effective rehabilitation experience. The integration of stepper motors allows precise control over movement, promoting gradual strength and flexibility improvement. Overall, this device enhances the rehabilitation journey by making therapy more accessible, efficient, and engaging for patients, ultimately contributing to better recovery outcomes.

VI. RESULTS

The evaluation of the electrical physiotherapy device demonstrated its effectiveness in supporting knee replacement patients during rehabilitation. The integration of three stepper motors allowed for precise control over hip, knee, and ankle movements, facilitating a structured and targeted recovery process. The four customizable modes, including the walking mode, provided flexibility in therapy, enabling patients to adjust their exercises based on their progress and comfort level. Additionally, the mobile application enhanced user engagement by allowing real-time adjustments to movement angles and repetition counts. Overall, the results indicate that this device significantly improves rehabilitation efficiency, promotes patient participation, and contributes to a smoother recovery journey.

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SOLAR POWERED PORTABLE INVERTER FOR KIOSK SHOPS

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Abstract*— A solar powered portable inverter for kiosk shops is an innovative device which is designed to supply sustainable electrical energy using renewable solar energy. This devices offers useful Ac output from solar, and also provide dc for small electronic devices. Here we use two 25W solar panels for the initial input and it is stored in a 20 Ah li ion battery pack, then a high efficiency inverter circuit invert it into a 220W output Ac. The project emphasizes compactness, portability and energy efficiency and making it suitable for off-grid operations. Through meticulous design optimization, this project underscores the feasibility and significance of integrating renewable energy into everyday power systems, paving the way for innovative and sustainable energy solutions.

I. INTRODUCTION

The demand for sustainable energy solutions has grown exponentially in recent years, driven by concerns over climate change, rising energy costs, and the depletion of fossil fuel reserves. Solar energy, as a clean and renewable resource, has emerged as a cornerstone of global efforts to transition towards greener power systems. Among the various applications of solar energy, the development of compact, portable systems has gained significant attention due to their versatility and potential to provide energy access in off-grid or remote locations. A solar-powered portable inverter is one such innovative solution, combining renewable energy harvesting with advanced power electronics to create a reliable and environmentally friendly energy source. A solar-powered portable inverter converts the direct current (DC) generated by solar panels into alternating current (AC) to power a range of devices, from household appliances to small electronic gadgets. This functionality is especially valuable in areas where grid connectivity is unavailable or unreliable, such as rural communities, disaster-stricken regions, and outdoor recreational activities. Unlike traditional power generators that rely on fossil fuels, solar-powered inverters operate silently and emit no greenhouse gases, making them ideal for reducing carbon footprints and supporting sustainable energy practices.

The design of a solar-powered portable inverter integrates several key components, including solar panels for energy generation, a charge controller to regulate energy flow, a battery storage system for energy backup, and an inverter circuit to convert DC to AC. Together, these components form a cohesive system capable of providing consistent and efficient power output. The compact and lightweight nature of the design enhances portability, enabling users to transport and deploy the system easily in various environments. Recent advancements in solar technology and power electronics have significantly improved the efficiency and affordability of portable inverters. Modern inverter circuits achieve high conversion efficiencies, ensuring minimal energy loss during the DC-to-AC conversion process. These technological improvements have made solar-powered portable inverters more accessible and practical for a wide range of applications.

Despite their numerous advantages, solar-powered portable inverters also face challenges, such as the variability of solar energy due to weather conditions and the limited energy storage capacity of batteries. Addressing these challenges requires innovative design approaches, including the use of advanced materials for energy storage, intelligent energy management systems, and hybrid configurations that incorporate auxiliary e'l,nergy sources. These solutions can enhance the reliability and performance of portable solar inverters, making them even more appealing to users. By

providing a practical and scalable solution for off-grid energy needs, these systems contribute to reducing energy inequality and supporting the transition to a low-carbon economy. This paper explores the design and functionality of a solar-powered portable inverter, highlighting its potential to address modern energy challenges and advance the adoption of renewable energy technologies. Through this effort, it aims to demonstrate the feasibility and benefits of integrating solar power into portable energy systems for a sustainable future.

II. LITERATURE SURVEY

The paper titled *"Design and Analysis of a Portable Solar Inverter"* delves into the development and evaluation of a compact solar inverter system designed for portable applications. Smith and Johnson present a design that integrates solar panels, a battery energy storage system, and a power inverter, with an emphasis on high efficiency and lightweight construction. The system is optimized for small-scale energy demands, like powering household electronics and supporting off-grid applications. One of the key features of the system is the high-efficiency Maximum Power Point Tracking (MPPT) algorithm, which maximizes solar energy utilization, as well as the inverter circuit, which is capable of delivering stable AC output under varying load conditions. The authors also explore thermal management strategies and protective mechanisms, such as overvoltage and short-circuit safeguards, to enhance the reliability of the system. Through both simulation and experimental analysis, Smith and Johnson demonstrate that the proposed system achieves high conversion efficiency and robust performance, even when faced with fluctuating solar irradiance scenarios. In conclusion, the authors highlight the potential of scaling this technology to address diverse energy demands while promoting renewable energy adoption. They position this research as a step forward in developing sustainable and portable solutions to global energy challenges.

The paper *"Power Electronics as Efficient Interface in Dispersed Power Generation Systems"* examines the crucial role of power electronics in improving the efficiency and reliability of decentralized power generation systems, especially those relying on renewable energy sources such as wind and solar. Blaabjerg, Chen, and Kjaer emphasize that power electronic converters are key components for interfacing these variable, decentralized energy sources with both the grid and standalone loads. The paper offers an overview of various converter topologies, control strategies, and their suitability for different types of dispersed generation systems. The authors discuss how advancements in power electronics contribute to enhanced energy conversion efficiency, power quality, and system stability. Topics such as Maximum Power Point Tracking (MPPT) for solar energy systems, grid synchronization, and fault tolerance are also addressed. In addition, the study explores challenges like managing harmonics, ensuring bidirectional energy flow, and integrating energy storage systems. In conclusion, Blaabjerg, Chen, and Kjaer stress the need for continuous innovation in power electronics to facilitate the transition toward a more decentralized and sustainable energy infrastructure. This paper serves as a comprehensive guide for understanding the role of power electronics in renewable energy systems.

In *"A Review of Single-Phase Grid-Connected Inverters for Photovoltaic Modules,"* Kjaer, Pedersen, and Blaabjerg provide a thorough review of inverter technologies used in single-phase grid-connected photovoltaic (PV) systems. The authors focus on the pivotal role inverters play in converting the DC power generated by PV modules into AC power that is compatible with the grid. The paper categorizes and evaluates various inverter topologies, including transformer-based and transformer-less designs, highlighting their respective advantages, limitations, and suitability for various applications. Key performance metrics such as efficiency, reliability, power quality, and cost-effectiveness are also discussed. Special attention is given to emerging transformer-less inverter designs, which offer higher efficiency and reduced weight, but require advanced safety measures to prevent leakage currents. The paper also delves into control strategies, such as Maximum Power Point Tracking (MPPT) techniques, which are essential for optimizing energy extraction from PV modules. Kjaer, Pedersen, and Blaabjerg address challenges such as harmonic distortion, grid synchronization, and ensuring compliance with international grid integration standards. In conclusion, the authors note that while significant progress has been made in inverter technology, ongoing research and development are essential to further improving efficiency, reducing costs, and ensuring the seamless integration of PV systems into the grid. This review provides valuable insights for researchers and engineers working to advance grid-connected PV technology.

III.METHODOLOGY

A. Block diagram

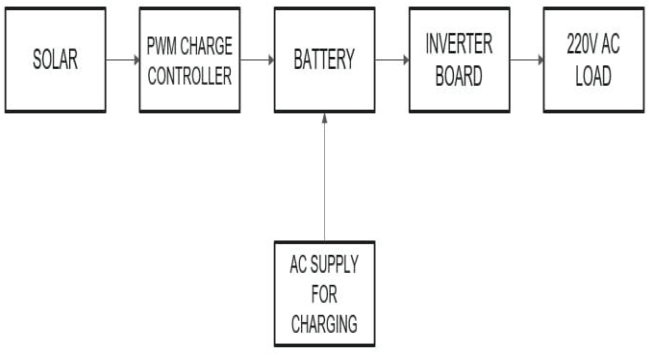

Fig.3.1 block diagram

The solar panel serves as the primary power source, converting sunlight into DC electricity. Solar energy is harnessed during the day when sunlight is available, and the electricity generated is directed to a Pulse Width Modulation (PWM) charge controller. The PWM charge controller regulates the voltage and current to charge the battery optimally, ensuring the battery is protected from overcharging, which could otherwise reduce its lifespan. By managing the energy flow, the charge controller ensures that any excess power generated by the solar panel is stored efficiently in the battery for later use. This stored energy becomes particularly useful when the sunlight is insufficient to meet the load requirements.

A battery is a critical component in this system, acting as an energy storage unit. It stores surplus solar energy during the day and supplies power to the loads during low or no sunlight conditions, such as cloudy days or nighttime. The battery ensures uninterrupted power to the system's loads, making the setup more resilient and reliable. Additionally, it serves as a buffer, smoothing out fluctuations in solar power generation due to varying weather conditions. The system also incorporates an AC supply as an auxiliary power source, providing flexibility and backup support. This dual-source capability ensures that the system remains operational even in periods of low sunlight, as it can draw power from the AC grid to keep the battery charged and the loads supplied.

Once the DC power is stored in the battery, it can be utilized in multiple ways depending on the type of load. For AC loads, the stored DC power from the battery is fed into a boost inverter. This inverter converts the low-voltage DC (typically around 12V) from the battery to high-voltage AC (220V) required by certain appliances. PWM charge controller provides a output of 5V via USB allows powering of low-voltage DC devices, such as small electronics that require 5V.

B. PWM charge controller

Fig 3.2 PWM charge controller

A Pulse Width Modulation charge controller aka the PWM solar charge controller used to be a very popular type of solar charge controller in the 90s.But first things first: PWM is an algorithm; not a device. When this algo is embedded in a solar charge controller, that controller is known as the PWM solar charge controller.

The purpose of a PWM charge controller, or any solar charge controller for that matter, is to bring the voltage of the solar power system down to correspond with the voltage of the load. The PWM charge controller modifies the input waveform to create a specific kind of waveform that is required for the output. In this way, PWM is utilised to regulate the formation of output waves, which subsequently regulates the load automatically.

Charging a solar-powered battery at the right level is significant. A PWM solar charge controller helped with this. Whenever the voltage of the batteries used to come to the set point of regulation, the PWM controller algorithm steadily lessened the charging current. It helped to prevent the battery from overheating and gassing.

Notably, there are three stages of charging in a PWM solar charge controller – the Bulk Charging stage, the Absorption Charging stage, and the Float Charging stage.

IV.RESULT AND ANALYSIS

Fig 4.1 implemented hardware

The result of implementing the solar-powered portable inverter system demonstrates its effectiveness in providing a reliable and sustainable power solution for kiosk shops. The system successfully converts solar energy into usable electrical power, efficiently managing energy storage and conversion processes. The PWM charge controller ensures optimal battery charging, preventing overcharging and deep discharging, which enhances battery lifespan. The dual charging capability, allowing both solar and AC supply for battery charging, adds flexibility and reliability, ensuring continuous power availability even in low sunlight conditions.

Testing of the inverter board confirms that it efficiently converts stored DC power into a stable 220V AC output, making it suitable for powering various household and small industrial appliances. The system's portability and off-grid

capability make it ideal for emergency backup power, remote locations, and outdoor applications. Overall, the results indicate that the system meets its design objectives by providing an efficient, portable, and eco-friendly power source, reducing dependence on conventional electricity grids.

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Automatic Glass Bottle Cleaning Machine

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***Abstract*— This paper proposes an innovative system for the automatic cleaning of glass bottles using high-pressure water jets and automated drying. Traditional bottle-cleaning methods often fail to clean hard-to-reach areas or require significant manual effort. This project introduces a solution that ensures thorough cleaning using high-pressure water jets to dislodge dirt and residue effectively. The system is designed for both domestic and commercial use, combining efficiency and ease of operation with energy-conscious design principles.**

***Index Terms* – bottle cleaner, automatic, cleaning machine, water reuse, efficient system**

I. Introduction

This project aims to develop an Automatic Glass Bottle Cleaning Machine (AGBC), designed to streamline and automate the otherwise labor-intensive process of cleaning water bottles, which is especially important in settings such as beverage manufacturing plants, hospitals, and water distribution facilities. The machine utilizes a combination of electrical and mechanical components to achieve an efficient and reliable cleaning operation with minimal human intervention.

At the core of the system is a 1HP motor, which provides the necessary rotational force to drive the cleaning mechanism that scrubs and rinses the water bottles. The motor is controlled by a BTS7960 motor driver, which allows for precise control of the motor's speed and direction, ensuring that the bottles are cleaned effectively while maintaining energy efficiency. The motor's operation is further regulated by a 12V,30A relay, which serves as an interface to switch the motor on and off based on the system's needs [10] .

Automation and control are achieved through the Arduino Uno microcontroller, which serves as the brain of the system. This Wi-Fi-enabled microcontroller can be programmed to manage the entire cleaning cycle, from starting the motor to activating the cleaning process and stopping it once the task is completed. The Arduino Uno allows for flexibility in terms of remote control and monitoring, offering the potential for integration into IoT (Internet of Things) systems for advanced applications. Two limit switches are used as feedback devices to ensure precise control of the motor's position and to define the start and end points of the cleaning cycle. These limit switches prevent the motor from running beyond the designated cleaning area, protecting both the machine components and the bottles themselves. When the motor reaches a certain position, the limit switches send signals to the Arduino Uno to either reverse or stop the motor, thereby automating the process without the need for manual intervention [9].

In addition to its functional features, the design focuses on safety and reliability. The use of the 12V 30A relay ensures that the motor can handle varying power demands without risk of overloading, while the BTS7960 motor driver ensures smooth and stable motor operation, even under load. The system also allows for flexibility in terms of cleaning parameters, such as the duration and intensity of the cleaning cycle, which can be customized depending on the application.

Overall, this automatic water bottle cleaning machine offers significant advantages over manual cleaning

methods. By incorporating automation, it reduces human labor, increases the speed and consistency of the cleaning process, and minimizes the risk of contamination or human error. The project demonstrates the effective integration of mechanical and electrical systems, providing a scalable solution for environments that require frequent and efficient bottle cleaning, with potential for further development and enhancement through IOT and machine learning for predictive maintenance and optimization. Since the size and weight are critical in such systems, here proposed topology will have inherent upper hand. The proposed converter can provide a much lower output voltage without adopting an extreme short duty ratio. Also it reduces the voltage stress across the switches and diodes. So switches with low voltage rating can be used. Low voltage rated switches have some advantages such as low cost, small ON-resistance, reduced reverse recovery time, low voltage drop etc. Thus efficiency of the converter increases.

Above mentioned advantages can be attained only if the blocking capacitors are charged initially and here comes the necessity of pre-charging circuitry. But the problem is that once the converter is started, pre-charging circuit will be idle and it is needed only during the next start. This paper introduces a new pre-charging circuit with (Resistor Capacitor Diode) RCD snubbed, which can perform pre-charging function during starting and can act as snubbed circuit during normal operation.

II. Proposed Topology

The Automatic Glass Bottle Cleaning Machine employs a systematic design to ensure thorough and automated cleaning of bottles. The process begins with a bottle placement system, where a mechanical holder or carousel secures the bottle in an upright or inverted position. Sensors detect the presence and size of the bottle, enabling the machine to adjust its operations accordingly[1].

The cleaning process is driven by a high-pressure water jet module. Strategically positioned nozzles spray water at high pressure to clean both the interior and exterior surfaces of the bottle. This ensures that all dirt, residue, and debris are dislodged effectively. Following the high-pressure cleaning, the bottle undergoes a rinsing phase, where clean water is sprayed to remove any remaining soap or particles, leaving the bottle hygienic and odor- free.

To eliminate moisture, the system incorporates a drying mechanism that uses heated air. This drying system ensures that the bottle is ready for immediate reuse. The entire operation is managed by a microcontroller-based control unit, which sequences the tasks, monitors sensor feedback, and adjusts the cleaning process based on the bottle's size and material.

The machine also includes a wastewater management system that collects used water in a filtration unit. This system filters out debris and contaminants, allowing for the possibility of water reuse or safe disposal. To ensure uninterrupted operation, the machine is powered by a stable power supply with an optional battery backup.

This topology provides an efficient and reliable approach to cleaning water bottles of varying sizes and shapes, ensuring hygiene, ease of operation, and sustainability.

Fig. 1: Structure of Machine

III. Steady State Analysis

Steady-state analysis in the context of the Automatic Water Bottle Cleaning Machine refers to the examination of the system's performance once it has reached equilibrium or stable operation. This involves understanding how the machine behaves when all its components, including water jets, sensors, drying system, and mechanical elements, operate in a continuous and predictable manner. The steady- state conditions are critical for assessing efficiency, power consumption, water usage, and the overall operational capacity of the system [2].

A. Operational Flow and System Components

In a steady-state, the system has completed its startup processes and all components are functioning at their

optimal operating levels. The key components involved in the steady- state operation of the cleaning machine include:

- Water Pump and High-Pressure Jets: The water pump delivers a constant, regulated flow of water to the high-pressure jets, which spray water inside and outside the bottle. The jets need to maintain a consistent water pressure and flow rate to ensure effective cleaning. In the steady-state, the pressure and flow parameters are stabilized and do not fluctuate drastically, ensuring uniform cleaning performance.
- Sensors: The ultrasonic or capacitive sensors used for detecting bottle size, positioning, and cleaning effectiveness remain in constant communication with the microcontroller. They monitor whether the bottle is correctly placed, the water flow is adequate, and the bottle is clean. Once steady-state is reached, the sensor outputs will be stabilize, indicating that all bottle characteristics are successfully measured and adjustments are made automatically during the cleaning cycle.
- Drying System: The drying system, powered by heated air blowers or fans, operates in a steady state when it reaches the right airflow and temperature to ensure complete drying of the bottle. The air blower speed and heat level stabilize once the drying cycle begins, ensuring that the bottle's drying process is completed without fluctuation, making it ready for reuse.
- Microcontroller and Control System: The microcontroller oversees the entire system's operations, including coordinating the cleaning cycle, rinsing, drying, and handling of sensors. In steady- state operation, the microcontroller continuously monitors all system inputs (sensor data) and outputs (motor controls, jet pressure, drying mechanisms), ensuring a smooth cycle. It adjusts operations as necessary, for example, by regulating water pressure or drying air speed, based on feedback from sensors [3].

B. Energy Consumption and Power Flow

In a steady-state, the power consumption of the system becomes predictable and efficient. The water pump, drying system, and motors draw power from the system's energy source, which is typically electric, potentially supplemented by solar energy in some designs. The power requirements stabilize when the system reaches a consistent operation mode. Key considerations during steady-state analysis include:

- Energy Efficiency: The steady-state performance should be optimized for minimal energy wastage. The high-pressure water jets should operate with constant efficiency, meaning the water pump draws just enough power to maintain the required pressure. Similarly, the drying system uses energy efficiently to dry the bottle within a specific time frame without excessive energy consumption.
- Battery Usage: If the system uses a rechargeable battery, steady-state analysis will show how long the battery lasts under continuous operation, and how effectively the battery is recharged (especially if using a solar panel). Understanding the energy consumption during steady-state helps in designing the battery size and charging cycles to ensure that the system runs reliably [9].
- Water Flow Rate and Pump Efficiency: In steady-state operation, the water pump should maintain a consistent water flow rate necessary to supply water to the cleaning jets. The efficiency of the pump becomes critical, as any energy loss during this phase increases the overall power requirements. The flow rate of water can be monitored and adjusted to ensure optimal cleaning, ensuring that the pump operates within its optimal performance curve.

C. Wastewater Management

During steady-state operation, the system's wastewater management capabilities become essential. The machine is designed to collect used water, which may be filtered and stored for reuse or disposed of properly. Key elements of wastewater management during steady-state include:

- Filtration Efficiency: The filters used to collect debris from the wastewater must operate at a steady rate, ensuring that the water jets are not clogged with contaminants. The steady-state analysis evaluates how well the system filters water over time and how long the filters last before needing maintenance or replacement.
- Storage or Disposal: The system Wastewater should be designed to manage the volume of wastewater generated during cleaning. In steady-state, the rate of wastewater generation should be consistent, and the storage or disposal system must accommodate this rate without overflow or leakage.

D. System Durability and Maintenance in Steady-State

As the system operates in steady-state, components should be durable enough to handle continuous use without significant wear or degradation. In this phase, the system reaches a point where wear and tear stabilize and are manageable. Maintenance is anticipated to be periodic rather than frequent:

- Pump and Motor Wear: In steady-state, the water pump and motors should function at consistent speeds and pressures without excessive friction or wear. The lifetime of these components depends on how effectively they operate under steady-state conditions. Regular maintenance checks ensure that parts are clean, free from debris, and well-lubricated.
- Sensor Calibration: Sensors used for bottle detection and cleanliness checks should maintain their calibration over time. In a steady-state scenario, these

sensors should operate with minimal drift, maintaining the accuracy of feedback provided to the microcontroller.

- Drying System Maintenance: The air blower or drying system needs to be operate at optimal airflow and temperature during steady-state. Over time, dust or moisture accumulation may affect its performance. Regular cleaning and maintenance will ensure that the drying system continues to function efficiently.

E. Steady-State Operational Efficiency

In summary, steady-state analysis of the Automatic Glass Bottle Cleaning Machine involves assessing the operational stability of key components, including energy consumption, water flow, sensor feedback, drying efficiency, and system durability. The goal is to maintain an optimized balance where the system operates efficiently, with minimal energy consumption and maintenance requirements. By analyzing how the system behaves when running in its steady state, engineers can fine-tune the design to ensure long-term reliability, user convenience, and sustainability.

Fig 2. Hardware setup

We have a futuristic concept that leverages advanced bottle cleaning technology for medical applications. Our innovation involves detecting the pressure of each nozzle to ensure that glass bottles receive the precise amount of water pressure required for optimal hygiene. This technology can be effectively utilized in medical settings where strict sterilization and hygiene standards are critical. Additionally, this system can be applied to the production of a new sustainable water product. By guaranteeing that each bottle meets high hygiene and reusability standards, we can significantly reduce plastic waste and contribute to a more sustainable future. Our approach not only enhances hygiene assurance but also promotes environmental responsibility by reducing single-use plastics.

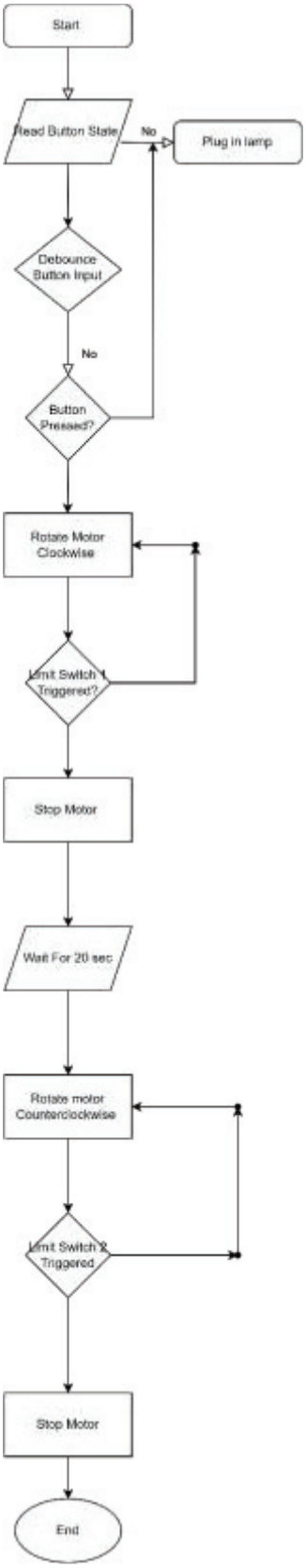

Fig 3. Flow chart of circuit

IV. CONCLUSION

The proposed automatic glass bottle cleaning system effectively overcomes the limitations of traditional methods by utilizing high-pressure water jets and an automated drying mechanism. This approach ensures thorough cleaning, even in hard-to-reach areas, while significantly reducing the need for manual effort. A key feature of the system is its water

reuse capability, which minimizes water wastage and enhances sustainability. Designed for both domestic and commercial applications, the system balances efficiency, ease of operation, and energy-conscious principles. By improving hygiene standards, optimizing resource utilization, and streamlining the cleaning process, this solution presents a practical and eco-friendly advancement. Future developments may focus on integrating smart sensors for real-time monitoring and further enhancing energy efficiency, making the system even more adaptable and sustainable.

Fig 4. Pressure of water

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***Abstract*— An intravenous drip monitoring system prototype has been developed for low drip rates. This ESP 32 microcontroller based IV drip system will be an accurate lowcost gravity-based solution that can be used in under-developed settings. This system uses a Load cell sensor, HX711 converter module, 20×4 LCD display with I2C and 12v buzzer implemented on an ESP 32 Microcontroller to detect weight of the IV bag and give alert when the content in the IV bag reaches below 25 percentage. Load Cell sensor is used to measure the weight of IV bag. HX711 converter module converts analog signal produced by load sensor to digital signal. LED display module shows the details of the content in the IV bag. 12V buzzer alert us with a beep sound when the content in the IV bag is below 25 percentage This system helps to ensure timely medical attention and also to improve resource management and patient safety. This innovative approach can transform traditional healthcare practices and make them more efficient to support patients.**

Keywords—Intravenous drip monitoring, Internet of Things (IoT), Wireless Monitoring

I. INTRODUCTION

In the modern healthcare system, it is crucial to make sure that nutrition, drugs, and other substances are delivered to patients' bodies correctly because improper administration can result in dehydration, overhydration, reverse blood flow, and other problems. The IV drip system was formerly manually inspected by medical specialists. To assist them and lessen their inefficiencies, a smart IV drip monitoring device with buzzer alarms and real-time monitoring has been designed. The relevance of automating these processes is growing in a world that is becoming more and more automated. Mistakes made during manual processes might have serious repercussions. It can be challenging for medical professionals, including doctors and nurses, to administer IV drip systems when they are managing multiple patients at once. Our system is designed to make things easier for them. Our system uses a load cell sensor to determine the fluid level by weighing the IV bag. The amount of fluid left in the IV bag may be accurately determined thanks to this. Additionally, when the weight falls below a predetermined threshold, buzzers will sound an alert to the medical staff. It also offers notifications via mobile devices. Additionally, it includes an LCD display for convenient monitoring, which makes things easier for the caregivers.

This project proposes a system that uses a load cell sensor to measure the weight of the IV bag, providing an accurate reading of fluid levels. When the weight drops below a preset threshold, a buzzer sounds an alert to notify medical staff. The system also includes an LCD display for local monitoring and Blynk IoT connectivity for remote notifications via mobile devices. By implementing this smart IV monitoring solution, healthcare professionals can ensure timely IV bag replacements, reducing the risk of patient complications and improving hospital workflow

II. BACKGROUND

Several studies have explored the use of automated IV monitoring systems**.** Amano et al. [1] proposed a Bluetooth-enabled remote IV monitoring system that allows nurses to monitor multiple patients simultaneously, reducing their workload. Similarly, Silva et al. [2] introduced a low-cost neonatal IV monitoring system that improves accuracy in low-infusion rates. Anand et al. [3] designed an Arduino-based IV drip monitoring system integrating sensors for patient vitals and automated alerts via SMS. Abernha et al. [4] developed an RF-based IV monitoring system to optimize healthcare resources. Our system improves upon these existing works by integrating IoT-based real-time monitoring with ESP32, load cell sensor, and Blynk application for enhanced efficiency and reliability.

III. SYSTEM DESIGN

A. Proposed system

The IV Drip Monitor was developed to address inefficiencies in IV fluid monitoring. The system employs Wi-Fi-enabled real-time monitoring, allowing remote access for healthcare staff. The HX711 converter module processes data from the load cell sensor and transmits it to the ESP32 microcontroller, which displays the IV bag status on an LCD screen and sends alerts via Blynk.

B. Block diagram

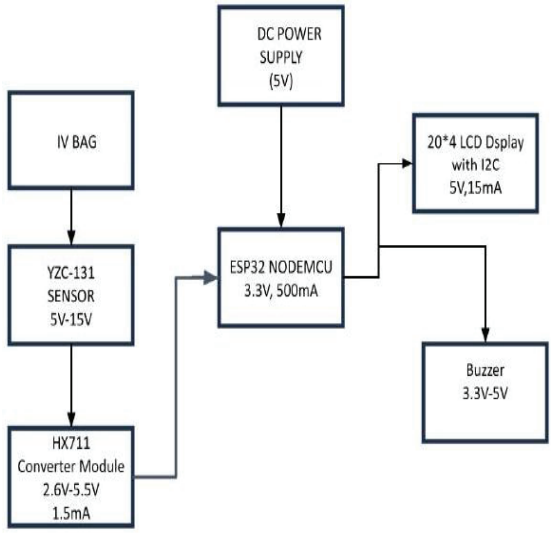

Fig.1.Block diagram

Load cell sensor is basically a Wheatstone bridge in balanced condition which detects any change in stress and changes the wheatstone bridge into unbalanced condition and very small current is produced. Since the signal is so small, a HX711 converter module is used. It amplifies as well as changes the signal to a digital signal. This signal is sent to Esp32 as well as the LCD display which displays the measurement and also to the buzzer which provides the warnings.Esp32 processes the data and passes it to mobile phones.

C. Circuit diagram

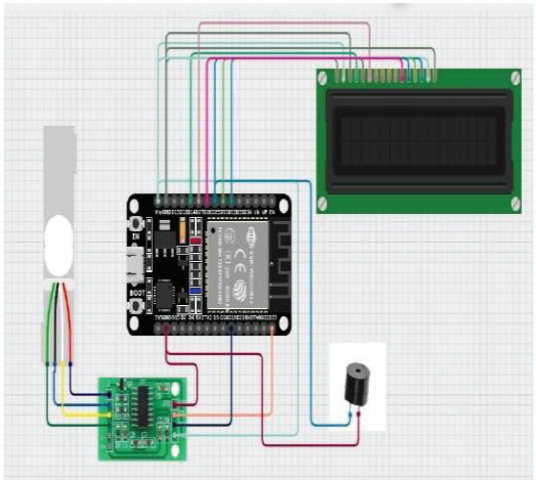

Fig.2.Circuit diagram

D. Hardware components

- ESP32 NodeMCU – Controls the entire system and enables IoT functionality.
- Load Cell Sensor (YZC-131) – Measures the IV bag weight accurately.
- HX711 Converter Module – Amplifies and converts analog sensor signals to digital.
- LCD Display (20×4) – Displays real-time IV fluid level.
- 12V Buzzer – Alerts medical staff when IV fluid drops below a threshold.
- Wi-Fi Connectivity – Enables real-time data transfer via Blynk

IV. IMPLEMENTATION AND TESTING

A. Breadboard Implementation

The initial prototype was developed on a breadboard to validate the system's functionality. Tests confirmed that the load cell sensor provided accurate weight readings, and the buzzer activated at the correct fluid level threshold

B. PCB Implemetation

After successful breadboard testing, a PCB version was designed using EasyEDA for a compact and reliable solution..

C. Flow chart

Fig.3.flow chart

D. Result

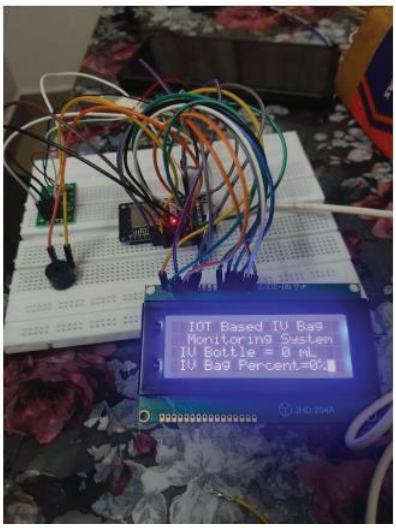

Fig.4. breadboard implementation

E. Table 1 Cost estimation

Sl No.	Item	Specifications	Qty	Cost Per Unit(in Rs)	Total (Rs)
1	ESP32 NodeMCU	3V-3.6V	1	368	368
2	YZC-131	5-10V	1	139	139
3	Buzzer	5-12V, 15-20mA	1	15	15
4	HX711 Converter Module	2.6-5.5V	1	44	44
5	LCD Display	5V	1	360	360
6	Jumper Wire		2	65	130
7	Breadboard		2	35	70
8				Total	1126

V. CONCLUSION

The proposed smart IV drip monitoring system enhances patient safety by automating IV fluid level tracking. It reduces the need for manual supervision, ensuring timely alerts and interventions. Future improvements could include AI-based predictive monitoring, multiple IV bag tracking, wireless power solutions, and integration with hospital management systems

VI. AKNOWLEDGMENT

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