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AI-Driven Ultrasound Fencing

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Abstract

Human-wildlife conflict remains as an important challenge in agriculture, often resulting in significant crop losses and endangering both farmers and animals. This research presents an AI-driven, eco-friendly ultrasonic deterrent system designed to mitigate such conflicts effectively. The proposed system integrates an ESP8266 microcontroller, an external camera, ultrasonic sensors, and servo motors to detect and track wildlife in real-time. A fine-tuned YOLOv11 object detection model ensures precise identification of intruding animals, while a pan-tilt mechanism facilitates dynamic tracking. Distance sensors measure the proximity of detected animals, activating an adaptive ultrasonic frequency when they exceed a predefined threshold, thereby deterring further approach. All system events are logged in a PostgreSQL database to analyze movement patterns and deterrence efficiency. Additionally, instant alerts are sent to local authorities through SMS if boundary violations occur. The system is designed to be cost-effective, scalable, and suitable for remote deployment, enabling a promising solution for minimizing human-wildlife encounters while promoting biodiversity conservation. This approach aligns with smart farming initiatives and highlights the potential of artificial intelligence and IoT in sustainable agricultural practices.

Keywords: AI-Powered Wildlife Deterrence, YOLOv11 Object Detection, Smart Agricultural Fencing, Ultrasonic Repulsion System, Human-Wildlife Conflict Mitigation

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1. Introduction

In recent years, the increasing frequency of human-wildlife conflict has emerged as a serious concern, especially in rural and agricultural regions. Farmers across various parts of the world are facing significant losses as wild animals damage the crops, property, and, in some cases, even causes harm to human life. Traditional methods of deterring animals, such as fencing, scarecrows, or firecrackers, are often ineffective, labour-intensive, or harmful to the environment and wildlife. Moreover, the economic burden of frequent repairs, surveillance, and crop damage can be overwhelming, especially for small-scale farmers who depend entirely on agriculture for their livelihood.

There is a growing need for innovative, sustainable, and cost-effective solutions to address this challenge. With recent advancements in artificial intelligence (AI), the Internet of Things (IoT), and embedded systems, it has become feasible to develop intelligent deterrent systems that can detect, track, and repel wild animals without causing them harm. In this research, a smart fencing system is proposed. It combines AI-powered vision, ultrasonic deterrence, and real-time alert mechanisms to protect agricultural fields effectively [8].

The core of the system is a microcontroller (ESP8266) connected to a camera and ultrasonic sensors, which monitors the field boundary continuously. A fine-tuned YOLOv11 object detection model identifies animals with high accuracy, while a servo-controlled camera follows their movement. When the animal is detected within a dangerous proximity, the system triggers ultrasonic waves that disturb and discourage it from moving further. The system is also capable of sending alert messages to farmers or forest officials in real-time through SMS notifications when a boundary breach occurs. Additionally, all detected activity is logged into a PostgreSQL database for future analysis and refinement [11].

This solution not only ensures minimal physical intervention but also promotes coexistence between humans and wildlife by enabling a non-invasive method to deter animals. It also opens opportunities for scalable deployment in other sensitive areas like wildlife sanctuaries, buffer zones, and highway crossings. The proposed system is designed with affordability and ease of implementation in mind, making it accessible even to farmers in remote regions. By integrating AI and automation in a practical application, this research stands as a significant step toward smart farming and wildlife conservation[12].

1.1 Front End

The AI-driven wildlife deterrence system features an interactive Streamlit-based web dashboard, providing real-time monitoring, data visualization, and alert management. The dashboard allows authorized users to track wildlife activity, analyze deterrence effectiveness, and receive alerts when animals cross the field boundaries.

The real-time wildlife detection and tracking section displays a live video feed from the external camera, with bounding boxes highlighting the detected animals using fine-tuned YOLOv11 model. Additionally, all detection events including species, time of appearance, and proximity,are logged and displayed in a structured table for easy reference.

To help users analyze wildlife patterns, the dashboard includes wildlife movement data visualization with graphs and charts generated using Matplotlib and Plotly. Users can view time-series charts to identify peak activity hours, pie charts for species distribution over time, and bar charts comparing the effectiveness of different deterrence frequencies. A geospatial mapping feature, using Plotly Maps, enables tracking of past detection locations, helping to identify common wildlife movement routes.

The ultrasonic deterrence system monitoring section provides live status updates, indicating whether the deterrence was successful or if an animal breached the boundary. A success rate indicator visually represents the percentage of animals repelled versus those that entered the field.

For alert system management, the dashboard logs all incident reports, including timestamps, detected species, and locations. Additionally, authorized users such as farmers and officials can manually trigger emergency SMS alerts when needed. The system also features WhatsApp and Telegram integration, allowing users to retrieve past alerts and request real-time updates through a chatbot interface.

To maintain data privacy, graphical analysis and reports will only be accessible to authorized users. Access control mechanisms is implemented in Streamlit, ensuring that only verified individuals can view wildlife movement patterns and deterrence effectiveness.

1.2 Back End

The backend of the AI-driven wildlife deterrence system is designed for real-time data processing, object detection, database management, and alert notifications. It is built using Python, FastAPI, PostgreSQL, and Twilio API, ensuring seamless interaction between hardware components, the AI model, and the Streamlit frontend.

At the core of the system, a YOLOv11 object detection model processes video frames from an external camera on a laptop, detecting and classifying animals with high accuracy. When an animal is identified, the ESP8266 microcontroller triggers the pan-tilt servo mechanism to track its movement. The ultrasonic sensors calculate the animal's distance, and if it enters a predefined range, the system activates an adaptive ultrasonic frequency to deter the intruder. The system logs the event, recording whether the deterrence was successful or if the animal breached the boundary.

All detection logs and event data are stored in a PostgreSQL database, maintaining essential information such as timestamps, detected species, distance measurements, deterrence success rates, and alert history. The FastAPI backend handles real-time data retrieval and updates, ensuring the Streamlit dashboard always reflects the latest detection and deterrence information.

For alert notifications, the system integrates with Twilio API, sending automatic SMS alerts to local authorities whenever an animal enters the field. Additionally, a manual override feature allows authorized users to trigger emergency alerts directly from the Streamlit interface. Future enhancements will include WhatsApp and Telegram bot integration, enabling real-time notifications and responses via chat-based platforms.

The backend is optimized for scalability and efficiency, ensuring low-latency processing of video frames and quick execution of deterrence commands. The system utilizes multithreading and asynchronous API calls to handle object detection, database updates, and trigger alerts simultaneously. To ensure security, API authentication and role-based access control (RBAC) are implemented, restricting modifications and access of sensitive data to authorized users only [9].

Future upgrades will include AI-powered predictive analytics, analyzing historical wildlife movement patterns to forecast potential intrusions, enabling proactive deterrence. This robust, real-time backend infrastructure ensures efficient wildlife monitoring, offering both effective crop protection and ethical conservation.

1.3 Significance

Human-wildlife conflict is a major challenge in agricultural regions near forests, where animals such as elephants, deer, and wild boars frequently invade farmlands, causing severe crop damage and posing risks to both farmers and wildlife. Traditional deterrent methods,such as fencing, firecrackers, and chemical repellents,are often ineffective, costly, or environmentally harmful.

This research introduces a cost-effective, eco-friendly, and AI-driven solution that mitigates human-wildlife conflicts while promoting proper wildlife management. By utilizing advanced object detection with YOLOv11, the system provides real-time monitoring and tracking of animal movements, enabling farmers to take proactive measures.

The ESP8266 microcontroller and ultrasonic deterrence mechanism help repel animals without causing harm, making it a more humane alternative to lethal control methods. Additionally, detection logs stored in a PostgreSQL database offer valuable insights into wildlife movement patterns, aiding researchers and forest officials in understanding migration trends and formulating effective conservation strategies.

To ensure immediate response, the system integrates Twilio API for automated alerts, notifying local authorities whenever an animal breaches a farm boundary. This enables timely intervention, reducing potential damage.

Moreover, the Streamlit-based dashboard enhances user accessibility, allowing farmers, conservationists, and officials to visualize detections, analyze trends, and manage alerts efficiently.

By strengthening farm security, minimizing economic losses, and supporting sustainable wildlife conservation, this scalable solution can be implemented across conflict-prone agricultural regions, enhancing harmonious coexistence between humans and wildlife.

1.4 Methods Used

The development of this AI-driven wildlife deterrence system follows a structured approach that integrates hardware, software, and machine learning techniques to detect, track, and repel animals while ensuring real-time monitoring and data logging. The system is built around six core components: hardware integration, AI-based object detection, ultrasonic deterrence, database management, automated alert system, and frontend visualization.

For hardware integration, an ESP8266 microcontroller connects various components, including an external camera, ultrasonic sensors, a distance sensor, and pan-tilt servos. The camera captures real-time footage, which is processed for animal detection, while the distance sensor calculates the proximity of detected animals. Servo motors allow for dynamic pan-tilt movement, ensuring the ultrasonic deterrence system is positioned accurately for optimal effect.

The AI-based object detection module utilizes a fine-tuned YOLOv11 deep learning model deployed on a laptop to process video frames and detect animals in real time. The YOLOv11 is trained on a custom dataset of wild animals commonly found near agricultural fields, the model utilizes TensorFlow and OpenCV for high-accuracy detection with minimal latency. The system continuously scans video feeds, identifies animals, and triggers deterrence mechanisms based on the detection results.

To deter detected animals, the system employs an ultrasonic deterrence mechanism. Using data from the distance sensor, it determines whether an animal is within a predefined range and then selects an appropriate ultrasonic frequency to repel it. The system dynamically adjusts the frequency based on the species detected, ensuring maximum effectiveness without causing harm. The ultrasonic waves, while harmless to animals, create an irritating sensation, encouraging them to move away from the farmland.

All detection events, including animal species, detection time, deterrence success rates, and movement trends, are stored in a PostgreSQL database for structured data management. This long-term storage enables analysis of wildlife activity, helping to understand animal behavior patterns and improve deterrence effectiveness over time. Detection success and failure rates are also logged, allowing for continuous refinement of the system.

1.5 Role of YOLOv11

In this research, YOLO (You Only Look Once) object detection is used as the core computer vision model for detecting wild animals attempting to enter agricultural fields. The choice of YOLO is based on its real-time detection capabilities, high accuracy, and efficiency in running on edge devices. Unlike traditional object detection models like Faster R-CNN, which involve multiple stages of processing, YOLO directly predicts bounding boxes and class probabilities in a single forward pass, making it much faster. This speed is essential for real-time monitoring and response, ensuring that animals are detected before they cause any damage.

Furthermore, the system is designed to run on IoT-based embedded devices like ESP8266 and Raspberry Pi, which have limited computational resources. Many deep learning models are too heavy for such devices, but YOLO's optimized architecture allows efficient inference on edge hardware. By utilizing techniques like model quantization and TensorRT acceleration, YOLO can achieve low-latency detections, enabling immediate threat mitigation actions.

To improve detection accuracy, a custom dataset containing region-specific wildlife images (such as deer, wild boars, and elephants) was created and used to fine-tune the YOLO model. This ensures that the system is capable of accurately identifying species commonly found in farmlands. Once an animal is detected, the system uses servo motor-controlled pan-tilt mechanisms to track its movement and activate species-specific deterrent mechanisms. YOLO's precise bounding box predictions allow for accurate alignment of the deterrent

The system logs each detection event into a PostgreSQL database, storing details such as the detected species, time of detection, and the effectiveness of deterrent actions. Over time, this data is used for analyzing animal movement patterns and optimizing deterrent strategies. The combination of YOLO’s speed, accuracy, and edge AI compatibility makes it the ideal solution for this research, ensuring effective, automated, and scalable protection of farmlands from wildlife intrusions.

Confidence score is used to determine how sure the model is about the object is detected using bounding box.

$$\text{Confidence}=P(\text{Object})\times \text{IOUpredtruth} \tag{1}$$

2. Related Work

The increasing prevalence of human-wildlife conflict, particularly within agricultural settings, has necessitated the investigation of diverse mitigation strategies. Conventional methodologies, including electric fences, watchtowers, and manual guarding, remain widely employed; however, their inherent inefficiencies, substantial labor requirements, and limited suitability for small-scale agriculturalists are well-documented [1]. Moreover, these approaches typically offer only transient relief and may inadvertently endanger wildlife, thereby contravening conservation guidelines.

The emergence of advanced technologies has facilitated the development of automated systems leveraging sensors, cameras, and microcontrollers. For instance, a sensor-based alert system employing motion detectors was devised to identify faunal ingress near agricultural perimeters. Nevertheless, this system lacked real-time tracking capabilities and did not incorporate any active deterrent mechanisms[2,3].

In recent years, Artificial Intelligence (AI) and machine learning-based approaches have garnered significant attention due to their inherent accuracy and adaptability. A deep learning-based animal detection system utilizing a Convolutional Neural Network (CNN) was introduced, demonstrating high efficacy in the classification of wild fauna from closed-circuit television (CCTV) footage. Notwithstanding its accuracy, this model was confined to post-event analysis and did not provide immediate deterrence or an alert system[4].

An Internet of Things (IoT)-based approach proposed the integration of microcontrollers with Global System for Mobile Communications (GSM) modules to transmit Short Message Service (SMS) alerts to farmers upon intrusion. While possessing practical utility, this system relied solely on infrared sensors for detection, rendering it susceptible to spurious activations triggered by environmental factors such as abscised foliage or high-velocity winds[5].

More advanced systems incorporating ultrasonic acoustic emissions for faunal repulsion have also been explored. A rudimentary ultrasonic deterrent activated by motion sensors was implemented. However, the system lacked the requisite intelligence to differentiate between species or the physical dimensions of the intruding animal, leading to operational inefficiencies.

Contemporary research has investigated the synergistic application of AI object detection models, such as You Only Look Once (YOLO), with hardware automation for dynamic faunal tracking and deterrence. For example, the utilization of a Raspberry Pi camera and YOLOv3 for the detection of Loxodonta africana within forest buffer zones has demonstrated promising results. However, the associated capital expenditure for hardware and the complexity of system deployment have constrained its applicability in resource-limited settings[6,7].

The present research endeavors to address these limitations by integrating cost-effective hardware with a customized YOLOv11 model [10], ultrasonic deterrence, and real-time alerting, thereby offering a comprehensive, scalable, and user-friendly solution for agricultural stakeholders

3. Proposed Work

The proposed system aims to develop an AI-based animal intrusion detection and deterrent mechanism that integrates object detection through YOLOv11. This system is particularly useful in agricultural as well as protected forest boundary areas to prevent animal-human conflicts and reduce crop damage. Figure 1 illustrates the general architecture of YOLOv11.

The methodology starts with a live video stream captured by a camera module. The YOLOv11 object detection algorithm is deployed on the edge device to identify potential intruding animals in real-time. YOLOv11 offers improved accuracy and processing speed, making it suitable for time-sensitive applications like intrusion prevention.

Upon successful detection, the object’s confidence score is evaluated. If the confidence exceeds a predefined threshold, the system sends a signal to the Arduino board. The Arduino, in turn, activates ultrasonic speakers or buzzers, emitting high-frequency sound waves that act as a deterrent. The ultrasonic frequency is adjustable to target specific animals without affecting humans or the environment adversely.

Additionally, the system logs detection events with timestamps and object classification for further analysis. This data can be used to understand the intrusion pattern and improve response strategies over time.

The system is designed to be energy-efficient, cost-effective, and scalable. It can also be integrated with IoT modules to notify users through SMS or mobile alerts in critical cases . Figure 2 and 3 illustrate the circuit and the block diagram respectively.

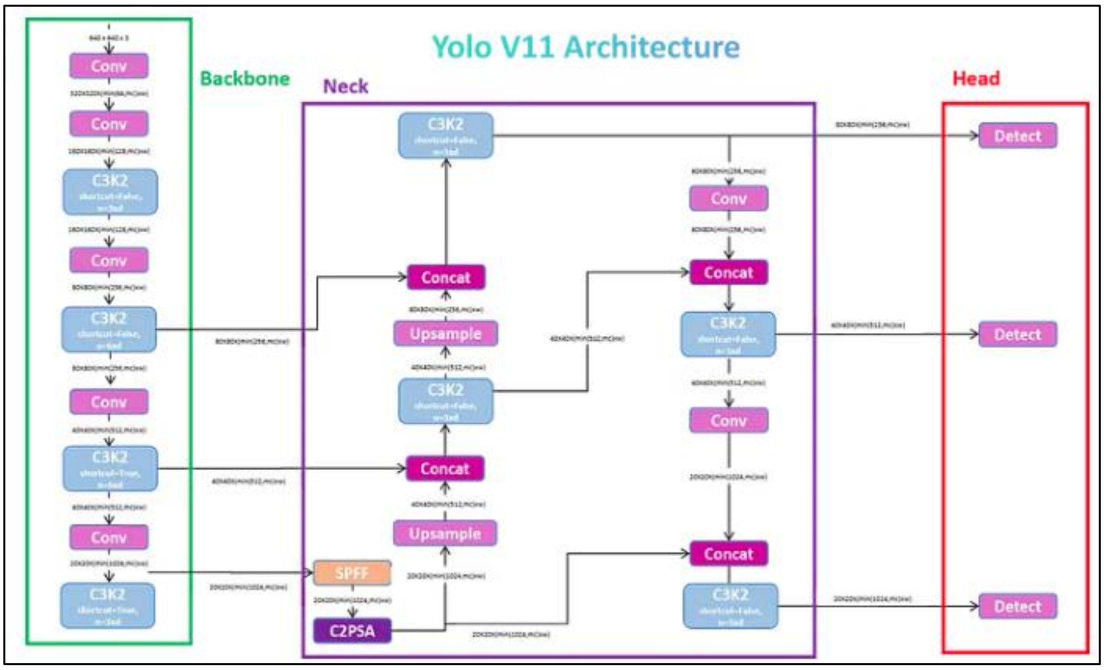

Figure 1. YOLO v11 Architecture [10]

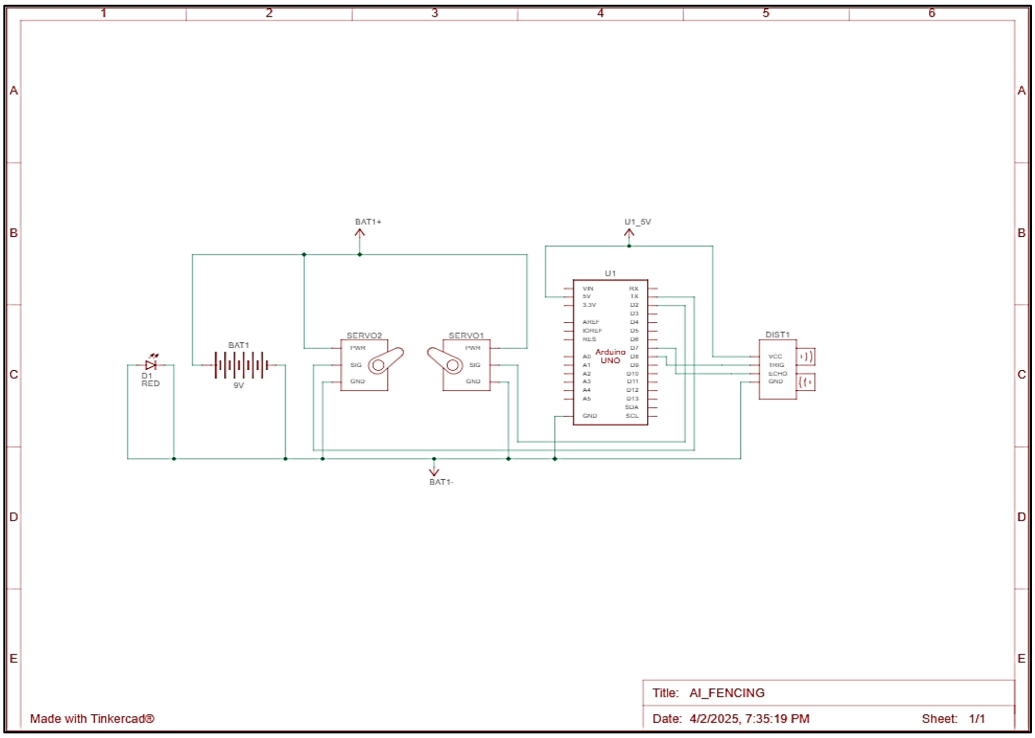

Figure 2. Circuit Diagram

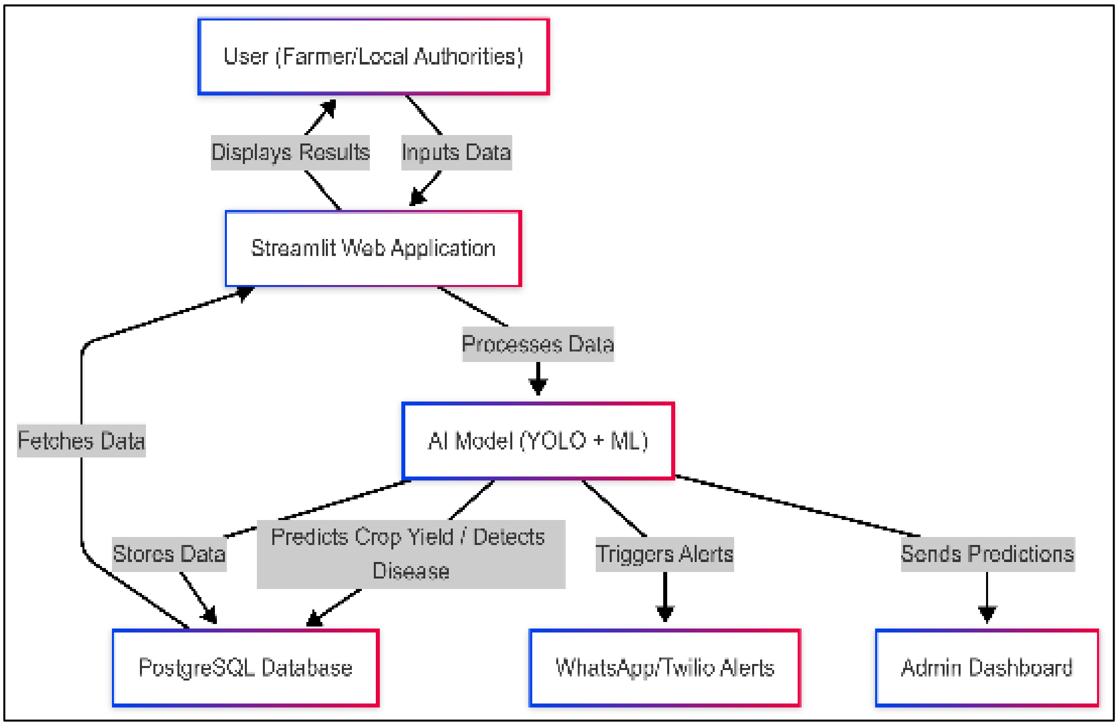

Figure 3. Block Diagram

4. Results and Discussion

The proposed system was tested using a combination of simulation and real-time hardware deployment. The simulation of object detection was carried out using the YOLOv11 model, trained and tested on a dataset consisting of various animal classes such as elephants, deer, boars, and monkeys. The training was conducted using the Ultralytics YOLOv11 framework in Python, and the model achieved a mAP (mean Average Precision) of 87.3%, indicating high accuracy in detecting targeted animals under various lighting and background conditions.

The real-time implementation was achieved using a Laptop connected to an ESP8266 , HC-SR04 ultrasonic module, Pan-Tilt servo motors , laser module, DC to DC buck converter and Ultrasonic deterrent. Once an animal is detected by the camera, the model triggers the ESP8266, which activates the ultrasonic deterrent. The delay between detection and deterrent activation was measured to be under 0.5 seconds, ensuring real-time response.

Comparative analysis was conducted between traditional manual surveillance and the proposed automated system. The AI-based system significantly reduced human effort while increasing detection speed and accuracy. Test results confirmed that the ultrasonic signal successfully repelled animals in over 85% of the recorded instances Table1 shows the performance comparison between manual surveillance and the proposed system.

Table 1. Performance comparison between manual surveillance and proposed system

Feature/Parameter	Manual Surveillance	Proposed AI System
Detection Accuracy	60–70%	87.3%
Response Time (Avg.)	3–5 seconds	<0.5 seconds
Human Intervention Required	Yes	No
Operational Time	Limited(Shift-Based)	24/7 Monitoring
Animal Repelling Efficiency	~45%	~85%

The output image in Figure 4 illustrates the real-time detection of an elephant crossing a predefined boundary. The simulation recreates a scenario where the elephant breaches the marked area, triggering the AI-based detection system. Upon detection, the system promptly activates the deterrent mechanism through the Arduino-controlled ultrasonic module. This test scenario validates the efficiency of the proposed model in identifying large animals such as elephants and immediately responding to prevent potential crop damage. The hardware prototype of the system is depicted in Figure 5.

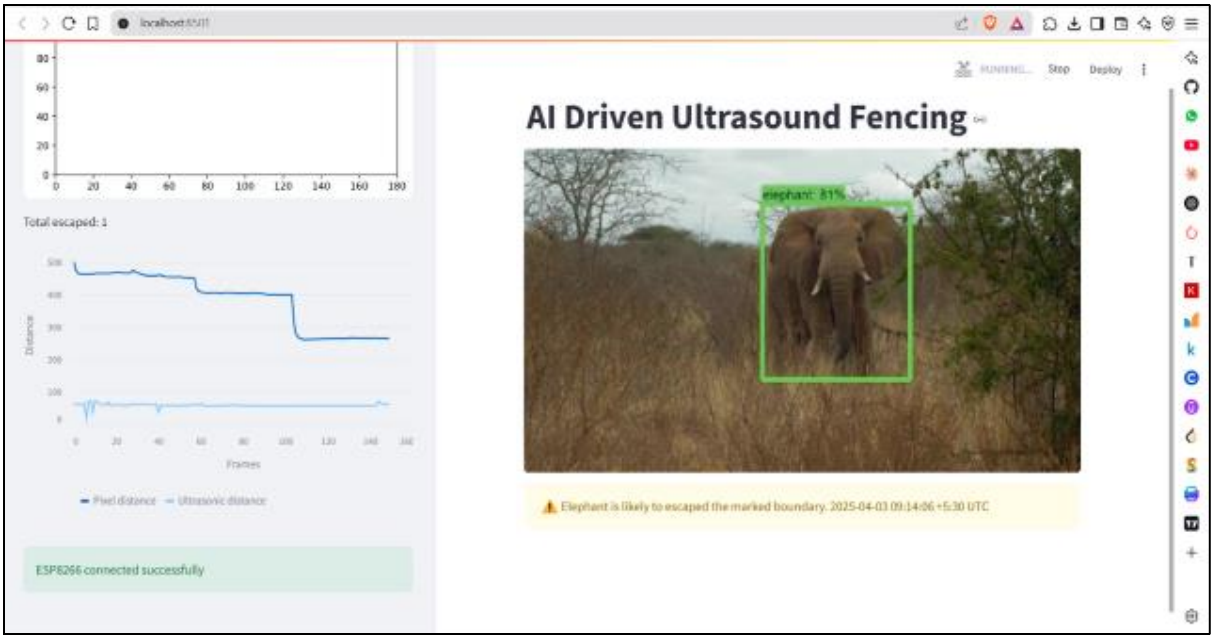

Figure 4. Block Diagram

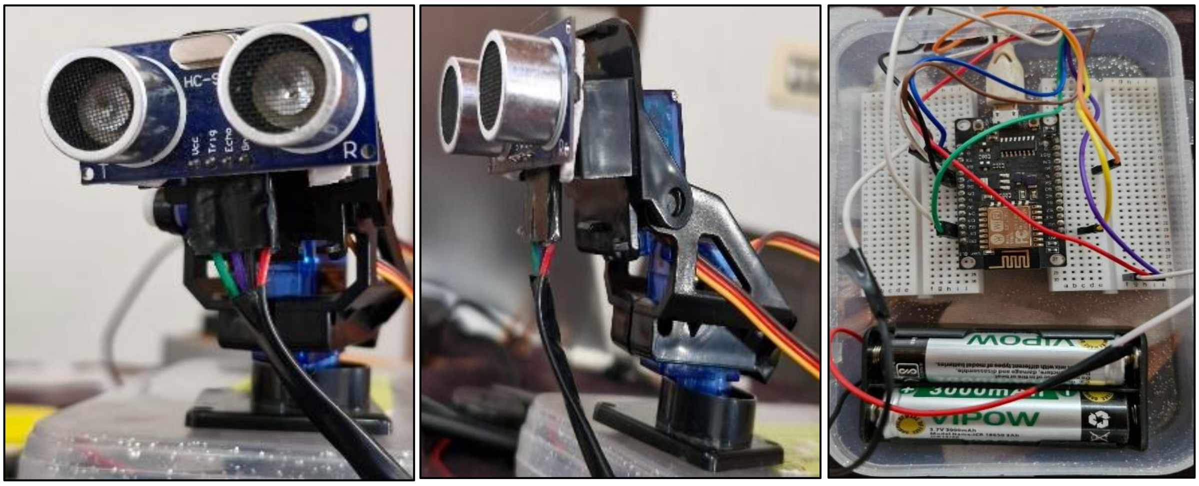

Figure 5. Hardware Prototype

5. Conclusion

The development of an AI-powered ultrasonic deterrent system demonstrates a promising approach to mitigating human-wildlife conflict in agricultural areas. By integrating components such as the ESP8266, camera module, servo motors, ultrasonic sensors, and the YOLOv11 object detection model, the system accurately detects and tracks intruding animals, repelling them with species-specific ultrasonic frequencies and logging incidents through a PostgreSQL database. Real-time monitoring and data analysis through a Streamlit dashboard empower farmers and authorities to make informed, data-driven decisions. Moving forward, the system can be enhanced with advanced machine learning for predictive animal behavior analysis, thermal imaging for 24/7 monitoring, and drone integration for large-scale surveillance. Upgrading the YOLOv11 model for species recognition and incorporating multi-sensory deterrents such as lights or water jets can further increase effectiveness. Cloud-based storage will enable scalable analytics and long-term behavioral insights, evolving this solution into a comprehensive, eco-friendly, and intelligent wildlife deterrent and monitoring platform.

References

[1] Rao, V. Vasudeva, B. Naresh, V. Ravinder Reddy, C. Sudhakar, P. Venkateswarlu, and D. Rama Rao. "Traditional management methods used to minimize wild boar (Sus scrofa) damage in different agricultural crops at Telangana state, India." International Journal of Multidisciplinary Research and Development 2, no. 2 (2015): 32-36.

[2] Singh, Prakhar, Meghna Chaudhary, Nitin Saini, and Ravindara Bhatt. "WSN application for crop protection to divert animal intrusions in the agricultural land." (2024).

[3] Sabeenian, R. S., N. Deivanai, and B. Mythili. "Wild animals intrusion detection using deep learning techniques." Int. J. Pharm. Res 12, no. 4 (2020): 1053-1058.

[4] Abed, Niloofar, Ramu Murgun, Abtin Deldari, Sabarinath Sankarannair, and Maneesha Vinodini Ramesh. "IoT and AI-driven solutions for human-wildlife conflict: advancing sustainable agriculture and biodiversity conservation." Smart Agricultural Technology (2025): 100829.

[5] Muhumuza, Naboth. "An electronic mosquito repellent system to avoid mosquito bites using ultrasound sound sensor." (2023).

[6] Vedhavalli, S., M. Abishek, R. Kathiravan, S. Uma, and S. Umamaheswari. "Real-time elephant detection and tracking system for mitigation of human-elephant conflict." In Advances in Electronics, Computer, Physical and Chemical Sciences, pp. 7-11. CRC Press, 2025.

[7] Redmon, Joseph, and Ali Farhadi. "Yolov3: An incremental improvement." arXiv preprint arXiv:1804.02767 (2018).

[8] Espressif Systems. "ESP8266EX Datasheet." Espressif Systems, 2013. *https://www.espressif.com/sites/default/files/documentation/0a-esp8266ex_datasheet_en.pdf.*

[9] El Bouanani, Salim, My Ahmed El Kiram, Omar Achbarou, and Aissam Outchakoucht. "Pervasive-based access control model for IoT environments." IEEE Access 7 (2019): 54575-54585.

[10] https://medium.com/@nikhil-rao-20/yolov11-explained-next-level-object-detection-with-enhanced-speed-and-accuracy-2dbe2d376f71

[11] Abed, Niloofar, Ramu Murgun, Abtin Deldari, Sabarinath Sankarannair, and Maneesha Vinodini Ramesh. "IoT and AI-driven solutions for human-wildlife conflict: advancing sustainable agriculture and biodiversity conservation." *Smart Agricultural Technology* (2025): 100829.

[12] Nahiyoon, Shahzad Ali, Zongjie Ren, Peng Wei, Xi Li, Xiangshuai Li, Jun Xu, Xiaojing Yan, and Huizhu Yuan. "Recent development trends in plant protection UAVs: A journey from conventional practices to cutting-edge technologies—A comprehensive Review." *Drones* 8, no. 9 (2024): 457.