An AI-Enabled Real-Time Alert System for Detecting Wild Animal Intrusions at Forest and Village Borders

Gnanasekar V[1], Geetha G [2], Dhivakar M[3], Pravin S[4], Prabu Anand R[5], Shyam Kumar S[6]

[1]*Head of the department (HOD), Department of Artificial Intelligence and Data Science, Hindusthan College of Technology Salem, India*

[2]*Assistant Professor, Department of Artificial Intelligence and Data Science, Hindusthan College of Technology Salem, India*

[3,4,5,6,7]*Department of Artificial Intelligence and Data Science, Hindusthan College of Technology Salem, India*

***Abstract*—AI-Enabled Real-Time Alert System for Detecting Wild Animal Intrusions at Forest and Village Borders an AI-enabled system to detect and notify users of wild animal intrusions in agricultural fields and village areas adjacent to forests, aiming to mitigate human–wildlife conflicts. The proposed solution enhances existing YOLO-based and edge computing frameworks by incorporating GPS-based location tracking and dual alert mechanisms. The system employs ESP32-CAM modules and ultrasonic sensors to capture motion-triggered images along established animal pathways. These images are processed locally using a YOLO object detection model to identify animals such as elephants, leopards, and wild boars with minimal latency. Upon detection of an animal, alerts specifying the animal type and location are dispatched via offline SMS over GSM/4G networks and through an online interface, delivering real-time visual and auditory alerts to civilians and forest rangers. Detection data is stored in the cloud for movement analysis and model enhancement. The system is cost-effective, scalable, and well-suited for deployment in rural areas.**

***Index Terms*—Wild Animal Intrusion, Human-Wildlife Conflict, YOLO, Edge AI, TinyML, IoT Sensors, GPS Localisation, SMS Alerts.**

I. INTRODUCTION

Human–wildlife conflict has become a major socio-economic and ecological issue worldwide. Rapid urbanization, agricultural expansion, deforestation, and climate change have significantly reduced natural wildlife habitats and food resources. As a result, animals such as elephants, leopards, wild boars, and deer frequently enter human settlements and agricultural lands in search of food and water. These unexpected intrusions cause severe crop damage, livestock loss, property destruction, and sometimes even human and animal casualties. In many forest-border regions, farmers suffer large economic losses due to wildlife attacks, highlighting the urgent need for effective monitoring and prevention systems.

Traditional methods used to prevent animal intrusion, such as forest ranger patrols, watch towers, and physical barriers, are labor-intensive and often ineffective for large areas, especially during nighttime. Early electronic systems using motion sensors like Passive Infrared (PIR) sensors can detect movement but cannot accurately identify whether the object is a wild animal or a harmless environmental disturbance. Recent developments in Artificial Intelligence (AI), Internet of Things (IoT), and computer vision have enabled the use of deep learning models for automated wildlife detection. In particular, real-time object detection models such as YOLO (You Only Look Once) provide fast and accurate identification of animals, making them suitable for real-time monitoring applications.

This project proposes an AI-based Animal Intrusion Detection and Alert System designed to reduce human–wildlife conflict through early detection and automated response. The system uses cameras and sensors installed near forest boundaries to detect movement, after which images are processed using a lightweight YOLO model on an edge device such as

ESP32-CAM. Image enhancement techniques like CLAHE and Retinex are applied to improve detection accuracy in low-light conditions. Once an animal is detected, the system identifies the species, determines the location using GPS, and sends alerts to forest officials and nearby residents through GSM networks and a web or mobile application. Additionally, non-lethal deterrents such as ultrasonic sounds and bright lights are activated to safely prevent animals from entering human settlements.

II. LITERATURE SURVEY

Hang Xu and colleagues (2019) introduced an intrusion-detection sensor system utilizing a broadband noise signal along with leaky coaxial cables (LCXs). Their method showed robust anti-radio frequency interference (anti-RFI) abilities, making it extremely appropriate for intricate RF settings. The system accomplished a precise range resolution of 30 cm and a dynamic range of 30 dB by sending and receiving a broadband noise signal through two parallel LCXs to create an invisible electromagnetic monitoring field. Nonetheless, the primary drawback of this method resides in the fundamental limitations of utilizing several LCX-based sensors simultaneously to enlarge protected zones, potentially resulting in interference with one another. Additionally, conventional detection devices are prone to physical damage and environmental disruptions, necessitating intricate underground setups for hiding.

Mai Ibraheam et al. (2023) introduced a streamlined animal species recognition model utilizing the YOLOv2 framework, tailored for embedded devices. Their method showed considerable enhancements in detection speed and the capability to handle geometric variations in animal forms. Through the combination of multi-level features, elimination of unnecessary convolutional layers, and incorporation of deformable convolutional layers (DCLs), the system realized a 5.0% increase in accuracy and a 12.0% boost in detection speed compared to the original YOLOv2. Nonetheless, the primary drawback of this method is the trade-off between optimal accuracy and computational efficiency, with larger models like YOLOv4 still surpassing it by 2.5% in basic accuracy. Moreover, the model was mainly developed to recognize only six particular animal species, requiring additional growth for wider wildlife uses.

B. Natarajan et al. (2023) introduced a hybrid deep learning model that integrates VGG-19 with Bidirectional Long Short-Term Memory (Bi-LSTM) networks to identify wild animal behavior and produce automated notifications. Their method showcased remarkable proficiency in managing both spatial image information and sequential temporal elements. Employing VGG-19 for animal classification and Bi-LSTM for activity tracking and creating text-based SMS notifications, the system attained an impressive classification accuracy of 98%, a mean Average Precision (mAP) of 77.2%, and a processing rate of 170 frames per second. Nonetheless, the principal drawback of this method is the increased complexity burden caused by merging various deep neural networks within a hybrid framework. Moreover, although the performance is excellent, occasional misclassifications happen, which can adversely impact the overall trustworthiness of the alert system.

Konkala Venkateswarlu Reddy et al. (2024) introduced a system for detecting and deterring animal intrusions that utilizes a TinyML-based deep learning model called EvoNet along with an IoT framework. Their method showed a great equilibrium between superior predictive accuracy and low resource utilization appropriate for edge computing. Employing a laser boundary system to activate an AI-CAM operated by the efficient EvoNet, in conjunction with a smart rover for immediate tracking, the system accomplished an impressive accuracy of 96.7%. The primary drawback of this method is the need to compress the model through pruning and quantization, resulting in a small decrease in accuracy from 91.4% to 90.1%. Moreover, performing physical interventions through the remote rover in dynamic or harsh environmental conditions continues to pose a significant challenge.

III. SYSTEM ARCHITECTURE:

The suggested Animal Intrusion Detection and Alert System is built on an extensive, six-tiered architectural structure.

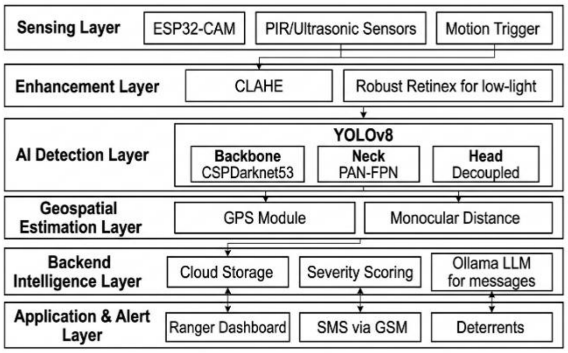

Figure 1. System Architecture

A. Sensing Layer:

To guarantee sustainable, long-lasting off-grid functionality, the physical hardware layer mainly functions in an energy-saving inactive mode. The sensing layer depends on energy-efficient edge devices, particularly the ESP32-CAM microcontroller, which acts as the main unit for visual data capture. Rather than constant video capturing, which quickly drains battery power, the system employs a hybrid wake-up method. Boundary nodes positioned strategically with Passive Infrared (PIR) sensors, ultrasonic sensors, or laser transmitters create an undetectable detection boundary. When an animal crosses this boundary, a hardware interrupt activates the camera to record live video feeds or a series of still images of the event.

B. Enhancement Layer:

Outdoor woodland settings pose notable visual difficulties, such as profound shadows, uneven illumination, and extremely low-light situations at night. To tackle this, the acquired visual information is directed through a specialized enhancement layer prior to AI inference. The system utilizes Contrast Limited Adaptive Histogram Equalization (CLAHE) to reassign pixel intensities and enhance local contrast. Subsequently, a Robust Retinex model is employed to decompose the image into reflectance and illumination components, effectively normalizing global lighting differences and reducing the disruptive impacts of vehicle headlight glare or thick foliage shadows.

C. AI Detection Layer:

The fundamental classification engine functions within the AI Detection Layer, utilizing the advanced YOLOv8 object detection algorithm for instantaneous inference. YOLOv8 is chosen for its exceptional combination of speed, precision, and resilience to scale variations and obstruction.

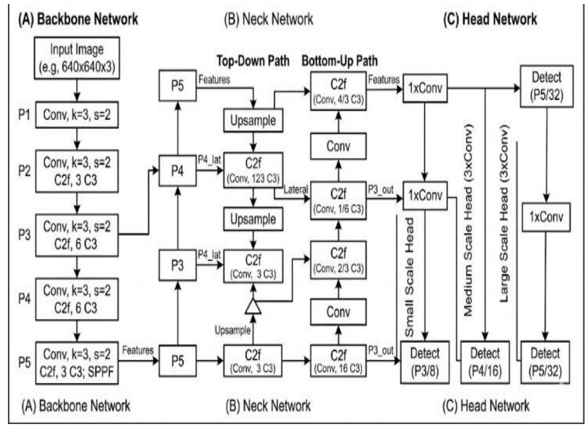

Figure 2. Yolov8 Structure

D. Geospatial Estimation Layer:

When a wildlife threat is confirmed, the system determines its exact location using a GPS module linked to the microcontroller. This module instantly records accurate real-time latitude and longitude of the detection event. In cases where stereo depth sensors are unavailable, monocular geometric methods are applied. Using the camera's field-of-view, focal length, and known animal dimensions, the system estimates distance. This distance is then combined with viewing angle and global bearing to compute geodesic coordinates, producing the animal's estimated position.

E. Backend Intelligence Layer:

The confirmed detection information, encompassing species classification and geospatial coordinates, is transmitted to a centralized backend server through REST APIs. This intelligence layer manages event retention, archiving intrusion logs for later ecological analysis and auditing. Additionally, it implements a severity scoring system based on rules. The system classifies threat severity as LOW, MEDIUM, HIGH, or CRITICAL by assessing the risk weight of the particular animal type (e.g., distinguishing a leopard from a deer), the detection confidence score, and the predicted closeness to human habitats. This score guides the creation of safety advisories that consider the context.

F. Generating Messages and Safety Measures:

To process the severity scores and raw data, the system utilizes Ollama to orchestrate local generative AI models (such as Llama 3 or Mistral). This approach ensures data privacy by keeping all processing on local infrastructure. These generative AI models take the raw detection logs, geospatial coordinates, and sensor data and convert them into natural-language reports and easy-to-read summaries tailored for villagers, forest officials, and researchers. Additionally, to distribute safety measures, the system utilizes a chatbot interface powered by these models that can provide specific safety instructions and answer common queries in local languages.

G. Application and Alert Layer:

The last layer oversees user interfaces and active response systems. Completely automated public warning systems pose the danger of false alerts and causing social panic. Detected events are forwarded to a specialized ranger dashboard that includes map visualizations and alert streams. After a forest ranger confirms the danger, the system permits the sending of offline SMS alerts to registered villagers in the high-risk area, and to a centralized web dashboard (Village's Dashboard)**.**

IV. PROPOSED SYSTEM

To effectively address the growing problem of human-wildlife conflict in areas adjacent to forests, this study suggests a thorough, AI and IoT-enabled Wild Animal Intrusion Detection and Notification System.

A. Combined Edge Detection and Equipment Installation:

The system utilizes inexpensive ESP32-CAM modules combined with Passive Infrared (PIR) and ultrasonic sensors placed strategically along the edges of forests, established animal migration routes, and entrances to villages. Instead of recording all the time, the system employs a motion-triggered activation method; when the PIR and ultrasonic sensors sense movement, the ESP32-CAM powers on to capture real-time camera feeds or brief video snippets of the intrusion. The complete hardware setup is enclosed in weather-resistant housings to guarantee longevity.

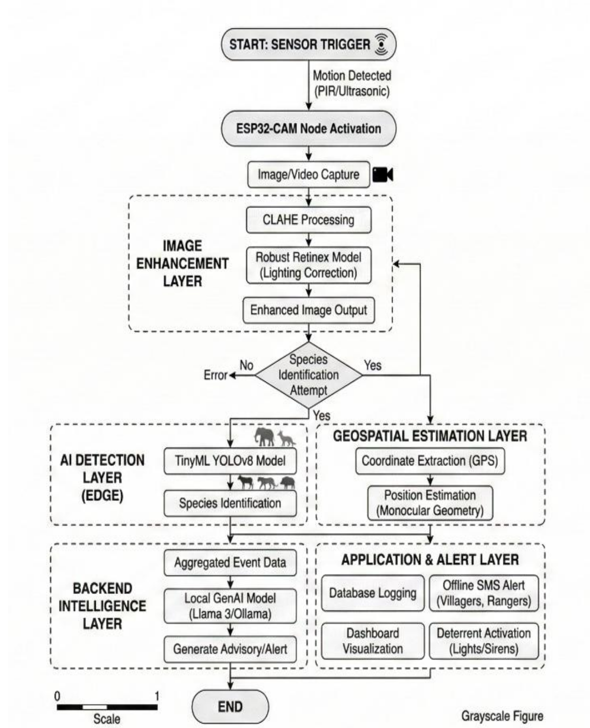

Figure 3. System Workflow

B. Visual Improvement and YOLO-Driven AI Detection:

As wild animals often appear at night or in poor weather, the collected visual data is processed through a brightness enhancement preprocessing pipeline. The system employs Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance local contrast and uses Retinex-based normalization to stabilize reflectance, guaranteeing that the AI model gets clear inputs despite shadows or low light. After enhancement, the images are analysed with a cutting-edge YOLO-based object detection model, specifically utilizing the YOLOv8 architecture defined in our architectural specifications.

C. Geospatial Assessment and Alert System:

The system pinpoints the threat's exact location using GPS coordinates and, when stereo depth sensors are absent, estimates distance through monocular geometric methods. Once an animal is classified with high confidence, a managed alert process begins, avoiding automated false alarms by including forest authority verification. Verified alerts are then sent via GSM/4G SMS and web dashboard with species and coordinates, while sirens activate locally to deter wildlife.

D. Integration of Cloud Analytics:

All verified detection events, metadata, and coordinates are continuously saved in a secure cloud database. This central database enables sustained data visualization, historical analysis for pinpointing high-risk areas, and ongoing retraining of the YOLO model.

V. MEDHODOLOGY

A. Requirements Analysis:

The first stage includes examining situations of human-wildlife conflict particularly in village areas adjacent to forests. Key species often causing intrusions, including elephants, leopards, and wild boars, are recognized for the detection criteria. Furthermore, functional and non-functional requirements are defined, emphasizing the viability of affordable, energy-efficient hardware appropriate for deployment in remote rural areas.

B. Hardware Configuration and Integration:

Energy Management: The hybrid IoT sensor network operates mainly in an energy-saving inactive state. High-power components activate only when required, ensuring efficient remote deployment.

Sensor Installation: Ultrasonic sensors are combined to measure distance accurately. This helps verify solid objects and reduces false alarms caused by environmental changes.

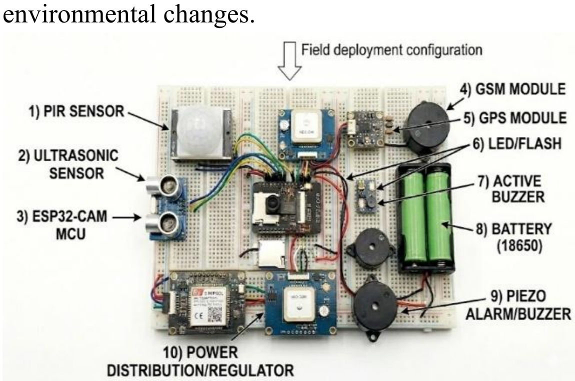

Figure 4. Hardware Setup

Vision and Processing: ESP32-CAM microcontrollers are installed along animal routes and forest edges. They wake from sleep mode on sensor interrupts to capture real-time intrusion images.

Communication & Localization: A GPS module adds precise coordinates to detection events. GSM/4G ensures offline SMS alerts reach rangers and villagers despite limited broadband access.

Hardware Setup: All components are enclosed in a robust, weather-resistant casing. This guarantees durability against heavy rainfall, extreme temperatures, and harsh outdoor conditions.

C. Dataset Compilation and Preperation:

Visuals and video clips of the designated wildlife species—specifically elephants, leopards, and wild boars—are collected from publicly available sources (like the Kaggle Animal Dataset and Missouri Camera Traps) and enhanced with relevant field information. To enable supervised learning, the original images are subjected to thorough manual annotation in which spatial bounding boxes and class labels are specified and converted into a precise YOLO-compatible text format.

D. Model Training (YOLO):

The system utilizes the You Only Look Once (YOLO) deep learning framework, famous for its single-stage detection ability that analyses complete images in one forward pass, thus providing an ideal balance between rapid inference and accuracy. The classification head of the network is set up solely for the chosen target animal classes to minimize unnecessary computational complexity.

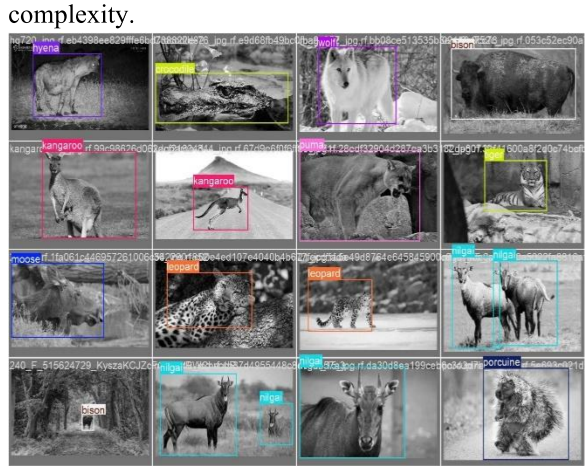

Figure 6. Training the Model with Different Animal Classes

The model undergoes iterative training on the improved dataset utilizing a pre-trained backbone (like CSPNet or DarkNet) to capture hierarchical features. To achieve a balance between predictive precision and computational demands, hyperparameters are carefully adjusted using the validation set; this encompasses employing the Adaptive Moment

Estimation (Adam) optimizer, determining an ideal learning rate (e.g., 0.001), and defining a specific batch size (e.g., 32) to guarantee steady convergence. During the training epochs, the learning performance of the network is consistently assessed using rigorous evaluation metrics: bounding box regression loss (for instance, Generalized Intersection over Union or GIoU loss), Precision, Recall, and mean Average Precision (mAP) at designated IoU thresholds (like mAP@0.5).

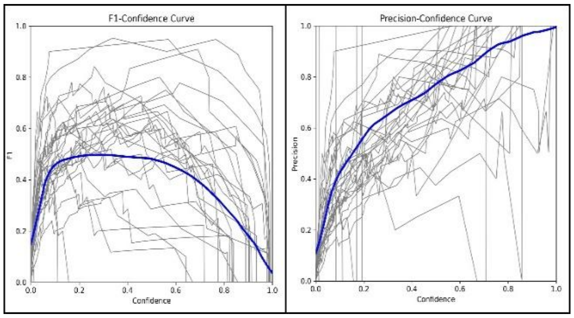

Figure 7. Confidence Curve and Precision Confidence Curve

When optimal convergence is achieved, the final trained weights of the neural network are locked and exported, prepared for additional compression (TinyML) for use on resource-limited edge devices.

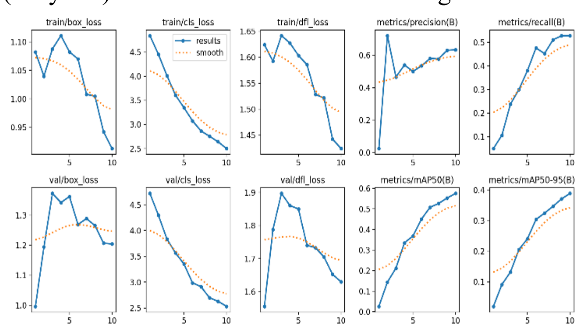

Figure 9. Result from Training the Modal with the Dataset

E. Edge Deployment and TimyML:

Optimization Implementing resource-heavy Convolutional Neural Networks (CNNs) on embedded microcontrollers like the ESP32-CAM poses a significant challenge owing to stringent memory constraints and limited processing capability. To effectively close this gap, the trained YOLO architecture is transformed into a lightweight inference model employing Tiny Machine Learning (TinyML) principles. The network experiences thorough model pruning, employing a polynomial decay schedule to methodically pinpoint and remove redundant or unimportant network parameters (weakest weights), thus considerably diminishing the computational burden.

F. Real Time Detection Process:

The sensing system conserves energy by remaining in standby mode until PIR and ultrasonic sensors detect movement or heat, triggering a hardware interrupt. This activates the ESP32-CAM, which captures real-time image frames for immediate local processing. A compact YOLO model classifies species, draws bounding boxes, and assigns confidence scores in one forward pass. Non-Maximum Suppression refines results by eliminating overlaps and retaining the most accurate detection. Simultaneously, the GPS module records precise coordinates, producing a validated threat profile ready for alert distribution.

G. Multi Modal Alert Creation and Proactive Deterrence

After successful classification, the edge unit checks the confidence score and only proceeds if it surpasses a threshold to filter false positives. This triggers a multi-modal response where generative AI converts raw detection logs, sensor data, and GPS coordinates into clear natural-language advisories. A dual-mode communication system then sends offline SMS alerts via GSM/4G with animal type, timestamp, coordinates, and safety instructions, while IoT features deliver detailed reports to a web dashboard. In parallel, the microcontroller activates non-lethal deterrents such as high-frequency acoustic sirens and intense visual light repellents. Together, these measures ensure timely alerts and effective wildlife repulsion without physical intervention.

H. Logging of Cloud Infrastructure

In addition to prompt tactical notifications, the framework encompasses an extensive data management pipeline for strategic environmental assessment. Each verified detection occurrence is sent to a centralized cloud database, forming a secure archive of collected images, species identifications, timestamps, and GPS data. This cloud architecture has two essential roles. It facilitates the creation of sophisticated spatio-temporal analyses, allowing authorities to track prolonged migration trends, precisely delineate high-risk intrusion areas, and proactively enhance the placement of physical barriers. Additionally, it creates a continuous learning model with a closed loop. The expanding collection of various field data, recorded under different local lighting and weather scenarios, is consistently employed to regularly retrain the YOLO detection model. This iterative tuning reduces algorithmic decline, gradually improving the model's accuracy and adaptability to its surroundings

I. Field Testing and Quantitative Verification

The final stage of the methodology involves extensive empirical evaluation of the integrated hardware and software in real-world agricultural settings near forests. Sensor nodes are deployed in high-risk areas to test reliability, while the AI detection model is assessed using metrics such as Precision, Recall, F1-Score, and mAP at IoU thresholds like mAP@0.5 and mAP@0.5:0.95. System latency is measured from motion detection to GSM/4G SMS alert transmission, with field tests aiming for a 3–5 second response. Hardware undergoes environmental stress testing to validate weather-resistant casings, and energy consumption of the ESP32-CAM and sensors is monitored. These evaluations ensure sustainable, durable, and efficient long-term functionality with off-grid solar systems.

J. Ongoing Performance Enhancement and Scalability

Utilizing the data collected during field validation, continual performance optimization is performed to meticulously improve system precision and effectiveness. To reduce the incidence of false positives caused by harmless environmental anomalies—like wind-driven foliage or significant changes in ambient temperature—confidence score thresholds and PIR sensor sensitivity levels are carefully adjusted. The inference latency of the TinyML YOLO model deployed at the edge is additionally enhanced by hyperparameter optimization and improved Non-Maximum Suppression (NMS) techniques to effectively remove redundant bounding box predictions. Ultimately, the communication structure of the system is evaluated to ensure strong scalability, confirming that additional sensor nodes can be effortlessly incorporated to create a wide-ranging, unobtrusive monitoring boundary throughout large agricultural areas

VI. RESULT AND DISCUSSION

A. RESULT

Preliminary field assessments using ESP32-CAM image captures and a YOLO-based classification model created a solid foundation for the system's fundamental functions. The detection model showed an average confidence score of 85% for typical target animal species. Examination of the assessment metrics revealed that the recall scores are very encouraging, showcasing the model's strong capacity to accurately detect candidate objects and recognize true positive cases in the environment. Nevertheless, the accuracy and mean average precision (mAP) metrics need enhancement, since the system sometimes produced false positives during the tests. Regarding hardware and communication efficiency, the system demonstrated remarkable responsiveness; tests in the field indicated that SMS notifications were effectively created and sent to users through the GSM module in a swift 3 to 5 seconds after the initial sensor activation.

B. DISCUSSION:

The experimental findings effectively confirm the operational soundness of the computer vision and suggested engineering pipeline. The ongoing instances of false positives and the requirement for enhanced precision are completely anticipated in the early phases of model training; these challenges are mainly due to the limited training time and the restricted size of the initial dataset. In addition to the software metrics, the overall IoT hardware framework showed outstanding operational reliability, verifying that the suggested architecture is extremely scalable and appropriate for edge deployment in remote, off-grid agricultural areas. Although the existing detection performance is adequate for validating the prototype, ongoing efforts will concentrate on improving the system further. To effectively decrease false positives and enhance overall precision, ensuing stages will focus on extensive data gathering under diverse and extreme conditions, prolonged multi-epoch training, and additional model adjustment for resilient real-world application

VII. CONCLUSION

This study introduces an AI-driven wildlife intrusion monitoring prototype designed to reduce human-wildlife conflicts in rural and agricultural areas near forests by integrating low-energy IoT sensing, edge-based computer vision, geospatial analysis, and backend intelligence into a cohesive framework. The system demonstrates key features such as real-time edge video processing, monocular positioning of intruders, context-sensitive advisory generation, and a regulated human-in-the-loop communication process, ensuring precise SMS notifications while minimizing false alarms and requiring limited human involvement. Although the pipeline functions end-to-end, detection accuracy remains in the prototype stage and requires refinement, yet the framework is scalable, modular, and well-suited for resource-limited edge environments. Future work will expand datasets across diverse conditions to enable multi-epoch training and hyperparameter tuning, reducing false positives and improving accuracy. Additionally, calibration with ground-truth GPS data will enhance geospatial precision, ultimately evolving into a resilient, proactive defense system for safeguarding agriculture and preserving wildlife.

REFERENCES

[1] W. Yang, T. Liu, P. Jiang, A. Qi, L. Deng, Z. Liu, and Y. He, “A forest wildlife detection algorithm based on improved YOLOv5s,” Animals, vol. 13, no. 19, p. 3134, Oct. 2023.

[2] R. Kavitha, N. S. Devi, N. Amirthakarthiga, and R. Srivarshini, “Wild animal detection using CNN,” Int. J. Res. Appl. Sci. Eng. Technol., vol. 11, no. 5, pp. 678–683, May 2023.

[3] S. Li, H. Zhang, and F. Xu, “Intelligent detection method for wildlife based on deep learning,” Sensors, vol. 23, no. 24, p. 9669, Dec. 2023.

[4] S. Sajithra Varun and G. Nagarajan, “DeepAID: A design of smart animal intrusion detection and classification using deep hybrid neural networks,” Soft Comput., pp. 1–12, May 2023.

[5] J. Chappidi and D. M. Sundaram, “Enhanced animal detection in complex outdoor environments using modified YOLOv7,” Int. J. Intell. Syst. Appl. Eng., vol. 12, no. 19, pp. 375–382, 2024.

[6] N. Sundaram and S. D. Meena, “Integrated animal monitoring system with animal detection and classification capabilities: A review on image modality, techniques, applications, and challenges,” Artif. Intell. Rev., vol. 56, no. 1, pp. 1–51, Oct. 2023.

[7] P. Kumar, S. Luo, and K. Shaukat, “A comprehensive review of deep learning approaches for animal detection on video data,” Int. J. Adv. Comput. Sci. Appl., vol. 14, no. 11, pp. 1420–1437, 2023.

[8] C. Carl, F. Schönfeld, I. Profft, A. Klamm, and D. Landgraf, “Automated detection of European wild mammal species in camera trap images with an existing and pre-trained computer vision model,” Eur. J. Wildlife Res., vol. 66, no. 4, p. 62, Aug. 2020.

[9] Y. Pulimi, S. R. Koppula, R. Katta, and R. Suryaneni, “Wild animal detection and alert system using YOLOv8,” Int. Res. J. Modernization Eng. Technol. Sci., vol. 6, no. 2, Feb. 2024.

[10] N. Banupriya, S. Saranya, R. Swaminathan, S. Harikumar, and S. Palanisamy, “Animal detection using a deep learning algorithm,” J. Crit. Rev., vol. 7, no. 1, pp. 434–439, 2020.