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

A. Nandha Kumar[1], S. Nirmal[2], M. Ruthra Prasath[3], M. Srikaran[4], Dr. K. Sasikala[5], Mrs. G. Kanmani[6]
Mrs. A. Santhi[7]
[1,2,3,4]UG Scholar, Department of Information Technology, R P Sarathy Institute of Technology, Poosaripatti, Salem-636305, Tamilnadu, India.
[5]Professor and Head, Department of Information Technology, R P Sarathy Institute of Technology, Poosaripatti, Salem-636305, Tamilnadu, India.
[6,7]Assistant Professor, Department of Information Technology, R P Sarathy Institute of Technology, Poosaripatti, Salem-636305, Tamilnadu, 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 Localization, SMS Alerts.**

I. INTRODUCTION

Human-wildlife conflict is now a socio-economic and ecological problem of great concern throughout the world. The high rate of urbanization, agricultural growth, deforestation and climatic change have greatly diminished natural living areas and food supply of wildlife. Due to this, animals like elephants, leopards, wild boars and deer so often visit human settlements and farmlands in search of food and water. Such unforeseen invasions lead to serious damage of crops, death of livestock, destruction of property and even death of human beings and animals. In most forest-border areas, farmers incur huge economic losses because of wildlife attacks, and therefore, an effective monitoring and prevention system is much needed.

Conventional ways of deterring animal intrusion like forest ranger patrol, watch towers, and physical barriers are laborious and in most cases ineffective in expansive places particularly at night. Initial electronic systems based on motion sensors such as Passive Infrared (PIR) sensors are capable of detecting movement but not distinguishing the object being a wild animal or an innocent environmental disturbance. The latest trends in Artificial Intelligence (AI), Internet of Things (IoT), and computer vision have allowed applying deep learning models to automated wildlife detection. Specifically, object detection models like YOLO (You Only Look Once) are real-time and can identify animals quickly and precisely, which means that they can be used in monitoring tasks that require real-time.
This project offers an AI-based Animal Intrusion Detection and Alert System, which is aimed at minimizing human-wildlife conflict by detecting and responding to it at an early stage. This system employs cameras and sensors mounted near forest edges and uses them to detect motion and then images are

processed by a lightweight YOLO model on an edge device like ESP32-CAM. Image enhancing methods such as CLAHE and Retinex are used to enhance the detection accuracy in low light environments. After an animal is detected, the system identifies the species, then locates the animal using the GPS, and arrives at the information to forest officials and nearby residents via a GSM network and web or cell phone application. There are also non-lethal deterring devices like ultrasonic sounds and light lights that are used to keep animals off human settlements safely.

II. LITERATURE SURVEY

A broadband noise signal and leaky coaxial cables (LCXs) were proposed by Hang Xu and colleagues (2019) as an intrusion-detection sensor system. Their technique demonstrated powerful anti-radio frequency interference (anti-RMI) capabilities and this technique proved highly suitable in complex RF environments. The system achieved an accurate range resolution of 30 cm and 30 dB dynamic range by transmitting and receiving a broadband noise signal using two parallel LCXs to form an invisible electromagnetic monitoring field. However, the main weakness of this approach lies in the inherent constraints of the use of multiple LCX-based sensors at once to expand secure areas, which can interfere with each other. Moreover, the traditional detection systems are also vulnerable to physical damage and environmental interference, which requires complex underground systems to conceal them.

Mai Ibraheam et al. (2023) presented a simplified animal species recognition model based on the YOLOv2 framework, but adapted to embedded devices. Their approach demonstrated significant improvements in the speed of detection and the ability to deal with geometric variation in the form of animals. The system achieved a 5.0% accuracy gain and a 12.0% improvement in detection speed over the original YOLOv2 with the combination of multi-level features, elimination of the unnecessary convolutional layers, and the use of deformable convolutional layers (DCLs). However, the major disadvantage of this approach is the accuracy/computational trade-off, as the bigger models such as YOLOv4 continue to outperform it by 2.5 percent in simple accuracy. Besides, the model was largely designed to identify only six specific animal species and this means that it must be extended to cover greater wildlife applications.

B. Natarajan et al. (2023) proposed a hybrid deep learning architecture that combines VGG-19 with Bidirectional Long Short-Term Memory (Bi-LSTM) networks to detect the behavior of wild animals and generate automated notifications. Their technique reflected an extraordinary competence in handling both spatial image data and sequential time. With VGG-19 used to classify animals and Bi-LSTM used to track activities and generate text-based SMS notifications, the system achieved an astonishing classification of 98, a mean Average Precision (mAP) of 77.2, and a processing rate of 170 frames per second. However, the major disadvantage of such an approach is the additional complexity cost associated with combining different deep neural networks in a hybrid architecture. Also, the performance is outstanding, but misclassifications do occur sometimes, which might negatively affect the general credibility of the alert system.

Konkala Venkateswarlu Reddy et al. (2024) proposed an animal intrusion detection and deterring system that employs a TinyML-based deep learning model known as EvoNet and an IoT system. Their method showed a great equilibrium between superior predictive accuracy and low resource utilization appropriate for edge computing. Using a laser boundary system to trigger an AI-CAM being controlled by the effective EvoNet, and a smart rover to track the system immediately, a great accuracy of 96.7 was achieved. The major disadvantage of the approach is that the model has to be compressed using pruning and quantization, which causes the accuracy to reduce by a slight margin of 91.4 to 90.1. In addition to that, the issue of physical intervention using the remote rover under dynamic or harsh environmental conditions remains a serious challenge.

III. SYSTEM ARCHITECTURE

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

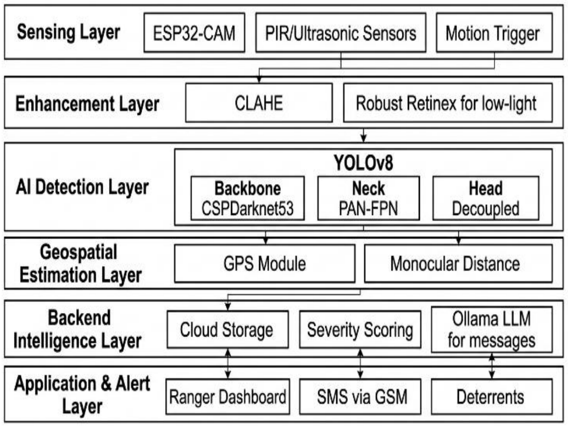

Figure 1. System Architecture

A. Sensing Layer

In order to ensure long-term off-grid operations which are sustainable, the physical hardware layer operates predominantly in power-saving idle mode. The sensing layer relies on energy-saving edge devices, especially the ESP32-CAM microcontroller that serves as the primary module of capturing a visual image. The system does not capture the video on a continuous basis, but rather follows a hybrid wake-up approach, which burns less battery power. Strategically positions and installed boundary nodes using Passive Infrared (PIR) sensors, ultrasonic sensors or laser transmitters form an invisible detection boundary. Whenever an animal goes across this boundary, a hardware interrupt triggers the camera to capture live video feeds or a sequence of still images of what has happened.

B. Enhancement Layer

The physical challenges of woodland environments include significant visual challenges, including deep shadows, imbalanced lighting, and incredibly low-light scenarios in the woods at night. To address this, the learnt visual information is channelled via an expert layer of enhancement before AI inference. Contrast Limited Adaptive Histogram Equalization (CLAHE) is used in the system to redistribute the pixel values and boost the local contrast. A Robust Retinex model is then used to break down the image into reflectance and illumination, in effect, equalizing lighting variations around the globe and minimizing the disruptive effect of vehicle headlight glare or dense undergrowth shadows.

C. AI Detection Layer

The basic classification engine operates in the AI Detection Layer, which uses the better YOLOv8 object detection algorithm to perform instant inference. YOLOv8 is selected due to its outstanding speed, accuracy and scalability to scale changes and challenges.

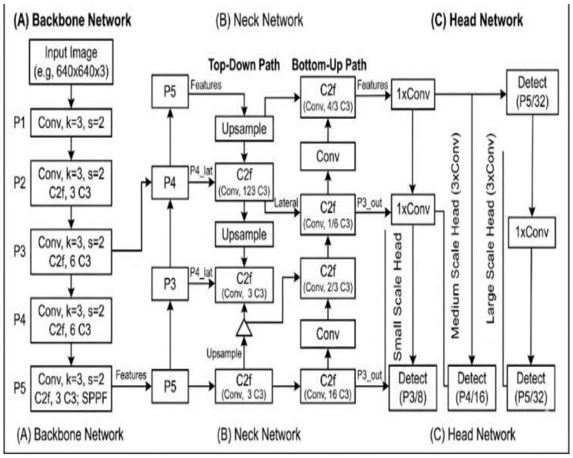

Figure 2. Yolov8 Structure

D. Geospatial Estimation Layer

In case the presence of a wildlife threat has been identified, the system identifies its specific position with the help of a GPS module connected to the microcontroller. This module instantly records accurate real-time latitude and longitude of the detection event. Where there are no stereo depth sensors, monocular geometric techniques are used. The system determines distance using the field-of-view, focal length and known animal dimensions of the camera. The distance is then used along with viewing angle and global bearing to calculate geodesic coordinates, which give the approximate location of the animal.

E. Backend Intelligence Layer

The verified detection data including species name and geospatial location are sent to a centralized backend server using REST APIs. This intelligence layer is used to retain events, store intrusion logs that can be used later to conduct ecological analysis and auditing. It also has a severity scoring system which is rule based. Threat severity is defined by the system as LOW, MEDIUM, HIGH, or CRITICAL based on the weight of risk associated with the specific type of animal (e.g., whether a leopard or a deer), the score on the detection confidence, and the estimated distance to human habitats. This score informs the drafting of safety advisories that take an environmental context into account.

F. Generating Messages and Safety Measures

The system uses Ollama to coordinate local generative AI models (e.g. Llama 3 or Mistral) to process the severity scores and raw data. This method offers privacy to data because all processing is maintained on local infrastructure. These generative AI systems receive the raw detection logs, geospatial position and sensor data and transform it into natural-language reports and readable summaries that are targeted at villagers, forest administrators and researchers. Also, the system uses the chatbot interface based on these models that can issue detailed safety guidance and respond to general inquiries in local languages to distribute the safety measures.

G. Application and Alert Layer

The last layer oversees user interfaces and active response systems. Full automation of warning systems to the population is dangerous in terms of false alarms and the development of social panic. The events detected are sent to a dedicated ranger dashboard which contains 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

In order to properly respond to the increasing issue of human-wildlife conflict in the territories near forests, this paper proposes a comprehensive, AI and IoT-powered Wild Animal Intrusion Detection and Notification System.

A. Combined Edge Detection and Equipment Installation

The system is based on the use of cheap ESP32-CAM boards and Passive Infrared (PIR) and ultrasonic sensors that are located in strategic points along the edges of forests, established animal migration paths, and village access points. The system does not need to record all the time, but rather it uses a motion-triggered activation technique in which the activation of the PIR and ultrasonic sensors succeeds the activation of the ESP32-CAM to capture real-time camera feeds or short video clips of the intrusion. The complete hardware setup is enclosed in weather-resistant housings to guarantee longevity.

B. Visual Improvement and YOLO-Driven AI Detection

Since the wild animals are frequently observed at night or during bad weather, the data in their visual form is first processed with a brightness enhancement preprocessing pipeline. The system uses Contrast Limited Adaptive Histogram Equalization (CLAHE) to increase the contrast of the local area and uses Retinex-based normalization to stabilize reflectance to ensure the AI model receives clear inputs even in the presence of a shadow or low-light areas. Once improved, the images are processed by an advanced YOLO-based object detector, namely on the basis of the YOLOv8 architecture specified in our architectural specifications.

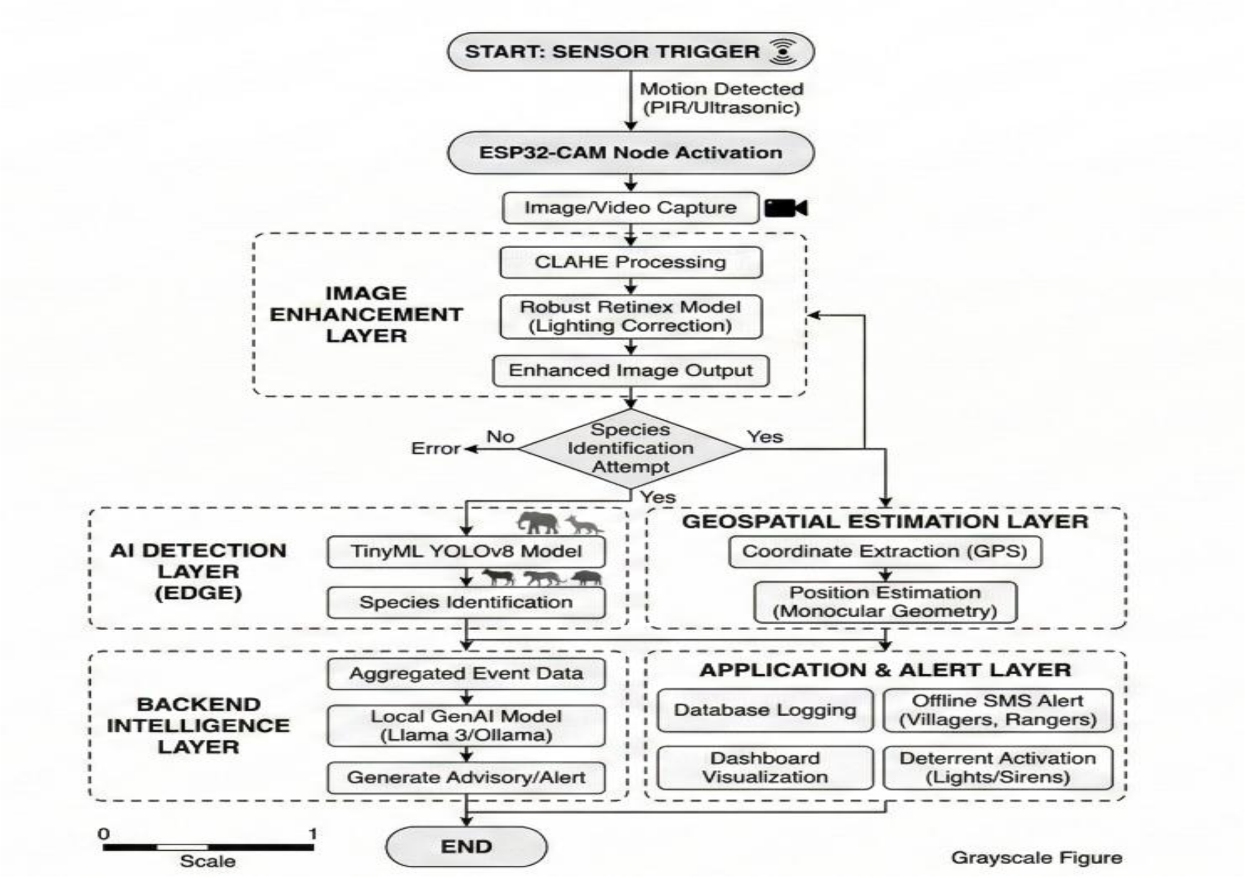

Figure 3. System Workflow

C. Geospatial Assessment and Alert System

The system identifies the exact point of the threat by GPS positioning and under normal conditions where there are no stereo depth sensors, the distance is estimated by the use of monocular geometric techniques. When an animal is high confidently identified, managed alert procedure commences and automated false alarms are avoided by incorporating verification by forest authority. Authenticated notifications are subsequently dispatched by GSM/4G SMS and web dashboard with species and coordinates, and sirens are triggered locally to chase wildlife.

D. Integration of Cloud Analytics

All confirmed detection events, metadata and coordinates are constantly stored in a safe cloud database. This central database will allow maintaining data visualization, historical analysis to identify high-risk areas, and retraining the YOLO model continuously.

V. MEDHODOLOGY

A. Requirements Analysis

The initial phase involves the analysis of the cases of human-wildlife conflict especially in the village regions near forests. The detection criteria are known to major species that typically lead to intrusions such as elephants, leopards and wild boars. Moreover, functional and non-functional requirements are outlined, with an accent on the feasibility of affordable and energy consuming hardware that can be deployed in remote rural locations.

B. Hardware Configuration and Integration

The initial phase involves the investigation of cases of human-wildlife conflict especially in village zones near forests. Elephants, leopards, wild boars, and other key species that are known to cause intrusions are known to be used in detection criteria.

Sensor Installation: The Ultrasonic sensors are integrated to detect distance. This aids in checking solid objects and minimizes false alarms brought about by changes in the environment.

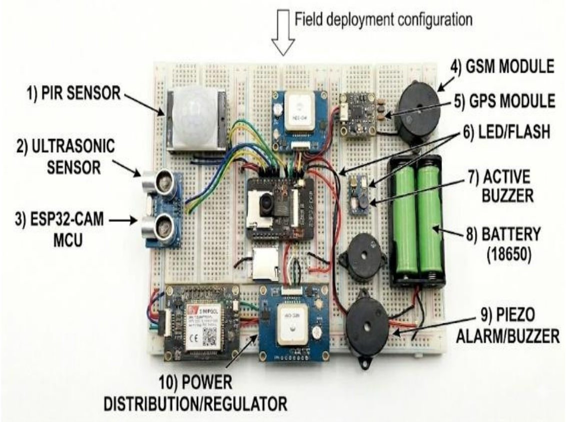

Figure 4. Hardware Setup

Vision and Processing: ESP32-CAM microcontrollers will be mounted in locations where animals move along and at the edges of forests. They exit the sleep mode of sensor interrupts to take real-time images of intrusions.

Communication & Localization: A GPS unit provides specific coordinates to detection events. GSM/4G will guarantee that offline SMS notifications are sent to rangers and villagers even when the broadband is not available.

Hardware Installation: All the parts are housed in a durable and weatherproof casing. This ensures that it is durable to heavy rainfall, extreme temperatures, and tough outdoor conditions.

C. Dataset Compilation and Preperation

Images and video records of the specified wildlife species, that is, elephants, leopards, and wild boars, are retrieved in publically accessible sources (such as the Kaggle Animal Dataset and Missouri Camera Traps) and complemented with the corresponding field data. In order to facilitate the supervised learning, the original images undergo comprehensive manual annotation where spatial bounding-boxes and labeling of class are delineated and converted into strict YOLO-compatible text format.

D. Model Training (YOLO)

The system is based on the You Only Look Once (YOLO) deep learning architecture, which is known to have a single-stage detection capacity (that is, images are processed to a single pass), thereby offering the optimal compromise between accuracy and speed of inference. Only the selected target animal classes are configured with the classification head of the network to reduce the computational complexity that is not needed.

Figure 6. Training the Model with Different Animal Classes

After this, the refined dataset is trainable multiple times using an already pre-trained backbone (e.g. CSPNet or DarkNet) to produce hierarchical characteristics. The validation set would be used to optimally tune hyperparameters; it would involve the Adaptive Moment Estimation (Adam) optimizer, a good learning rate (e.g. 0.001), and a fixed batch size (e.g. 32) to guarantee that the improvement is linear. The network learning performance is continuously assessed based on rigorous evaluation metrics in the training epochs: bounding box regression loss (e.g., Generalized Intersection over Union or GIoU loss), Precision, Recall, and mean Average Precision (mAP at 0.5).

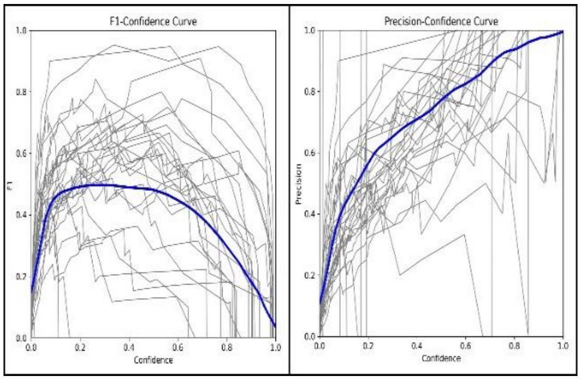

Figure 7. Confidence Curve and Precision Confidence Curve

Upon optimal convergence, the resulting trained weights of the neural network are frozen and made available to further compression (TinyML) to be used by resource-constrained edge devices.

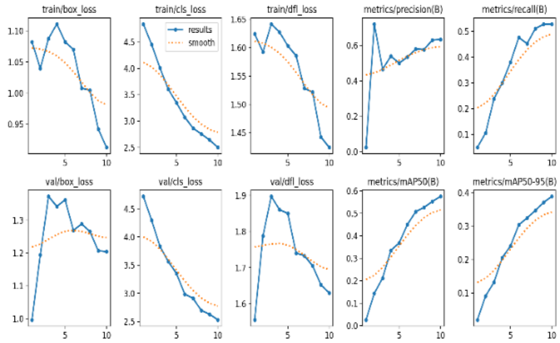

Figure 9. Result from Training the Modal with the Dataset

E. Edge Deployment and TimyML

The trained YOLO architecture is converted into a lightweight inference model relying on Tiny Machine Learning (TinyML) principles. A comprehensive pruned model is used, and a policy of the polynomial decay schedule is used to selectively identify and eliminate unnecessary or inconsequential network parameters (weakest weights), significantly reducing the computational cost.

F. Real Time Detection Process

Its sensing system saves on energy through standby mode until it is triggered by movement or heat on PIR and ultrasonic sensors to generate a hardware interrupt. This turns on the ESP32-CAM, which creates real-time frame photos that could be sent to local processing. One forward pass through a small YOLO model identifies species, bounding boxes, and confidence scores. Non-Maximum Suppression boosts the precision of numbers by removing overlaps and keeping the most precise detection.

G. Multi Modal Alert Creation and Proactive Deterrence

Once the classification has been successful, the edge unit will verify the confidence score and only continue to process the unit in case the score meets a threshold to eliminate false positives. This is a multi-modal reaction in which generative AI will turn uncoded detection logs, sensor data, and GPS coordinates into understandable natural-language guidance. A two-way communication system, in turn, transfers offline SMS notifications over GSM/4G with animal type, date, location, and safety protocols, whereas IoT functionality provides more detailed reports to a web dashboard. Meanwhile, the microcontroller would also turn on non-lethal deterrents, including high-frequency acoustic sirens and intense visual light repellents. All these measures are effective to guarantee prompt warning and successful repelling of wildlife without physical interventions.

H. Logging of Cloud Infrastructure

Besides timely tactic updates, the framework has a very large data management pipeline of strategic environmental evaluation. Every successful detection event is uploaded to a centralized cloud storage, as a secure record of the gathered images, species identifications, dates and GPS positions. The growing amount of diverse field data, captured and logged under varying local weather and light conditions, is continually used to retrain the YOLO detection model on a regular basis. This trial-and-error tuning alleviates the algorithmic degradation, slowly enhancing the level of accuracy and adjustability of the model to its environment.

I. Field Testing and Quantitative Verification

The last phase in the methodology is the widespread empirical testing of the combined hardware and software within the real-life agricultural environments close to the forests. The sensor nodes will be deployed in the risky regions to verify the reliability, and the AI detection model would be evaluated by the metrics Precision, Recalls, F1-Score, and mAP and iou thresholds. The measurement of system latency can be between motion detection and GSM/4G SMS alert transmission and field tests are expected to be 3 to 5 seconds to react. Environments are subjected to stress testing of hardware to prove weather-resilient casings, and power consumption of the ESP32-CAM and sensors is checked. Such tests guarantee cost-effective, long-term and sustainable operations of off-grid solar systems.

J. Ongoing Performance Enhancement and Scalability

Based on the data obtained in the process of field validation, continuous performance optimization is carried out so that system accuracy and efficiency are carefully enhanced. In order to minimize the occurrence of false positives due to non-hazardous environmental effect, such as wind-blown foliage or a dramatic shift in ambient temperature, confidence score thresholds and PIR sensor sensitivity levels are finely tuned. The hyperparameter optimization and better Non-Maximum Suppression (NMS) are further used to optimize the latency of the TinyML YOLO edge-deployed model to reduce unnecessary predictions on bounding boxes. Finally, system communication structure is tested to guarantee high scalability, which ensures that more sensor nodes can be added with ease to form a monitoring boundary that is vast and non-invasive to cover extensive agricultural fields.

VI. RESULT AND DISCUSSION

A. Result

Investigative field tests with ESP32-CAM image captures and a YOLO-based classification model established a good foundation of the basic operations of the system. The average confidence score of typical target animal species was 85% with the detection model. Analysis of the assessment measures showed that the recall scores are highly encouraging that demonstrates the high capability of the model to correctly identify candidate objects and identify the actual positive cases within the environment. However, the precision and average precision (mAP) statistics should be improved, as the system occasionally gave false positives in the tests. In terms of hardware and communication speed, the system displayed a very responsive nature; field tests show that SMS messages could be created and dispatched to subscribers via the GSM module in a very rapid 3 to 5 seconds upon the original sensor being activated.

B. Discussion

The results of the experiment adequately validate the functional soundness of the computer vision and proposed engineering pipeline. The current cases of false positives, and the necessity of higher accuracy are fully expected during the initial stages of training the model; the problem is largely contributed by the insufficient amount of training time, as well as limited size of the initial dataset. Besides the software metrics, the general IoT hardware platform demonstrated 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.excellent operational stability, confirming the fact that the proposed architecture is highly scalable and can be deployed to the edges in off-grid and remote agricultural regions. Even though the current performance of detection is satisfying to prove the prototype, continuous enhancement is going to be focused on further bettering the system. To achieve the desired reduction of false positives and overall precision, the next steps will involve a large-scale data collection in different and extreme settings, a long-lasting multi-epoch training, and further model tuning to solid and robust real-world presence.

VII. CONCLUSION

This paper presents an AI-controlled prototype of the wildlife intrusion monitoring system aimed at minimizing human-wildlife interactions in rural and agricultural regions adjacent to forests through the integration of low-energy IoT sensors, edge-computed vision, geospatial analysis, and intelligence of the back-end into a unified system. The system illustrates important characteristics, including real-time edge video processing, monocular placement of intruders, context-sensitive advisory generation, and a controlled human-in-the-loop communication process, which guarantee accurate SMS notifications and minimizes false alarms as well as limited human intervention. The pipeline is end-to-end; however, the detection accuracy is in the prototype phase and needs to be refined but the framework is scalable, modular, and fits resource-limited edge environments. Further research will widen the datasets in the different conditions and allow multi-epoch training and tuning of hyperparameters to decrease false positives and enhance accuracy. Also, it will be calibrated to ground-truth GPS data to improve geospatial accuracy, which will become a robust and proactive defence system to protect agriculture and conserve wildlife.

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