Indian Journal of Electronics and Communication Engineering (INDJECE)
Volume 3, Issue 2 (May- August 2026), PP: 47-53.
https://www.doi.org/10.59256/indjece.20260302006
https://fdrpjournals.org/indjece
ISSN NO: 3048-6408

Smart AI-IOT Approach for Deterring Wildlife Crop Raids

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To Cite this Article: *Rohit Uttam Patil[1], Dr. S. D. Bhopale[2], "Smart AI-IOT Approach for Deterring Wildlife Crop Raids", Indian Journal of Electronics and Communication Engineering, Volume 03, Issue 02, May-August 2026, PP: 47-53.*

Abstract*: Intrusion of wild animals into rural agricultural zones is a great threat to the agricultural yield since deer, elephants, wild boars, monkeys, etc., cause great harm to the crop. Fencing and physical protection do occur as well. Traditional methods of deterrence are not only costly and require much time but are also usually inefficient. This research focuses on the examination and creation of the system incorporating IoT and AI, using automatic deterrents, predictive analysis, and monitoring to protect crops from attacks by wild animals. Such a system combines the use of AI algorithms for recognition and classification of animals, drones, camera traps, movement prediction along with the use of IoT equipment with sensors, drones, and camera traps. Edge computing provides fast response even in the case of low connectivity of remote nodes.To increase nighttime detection accuracy and reduce any false alarms, a highly efficient multi-step perception pipeline would be used. This is based on video stabilization, low-light enhancement, hybrid CNN-Transformer, and temporal monitoring. It works to increase collaboration between humans and wildlife, while also ensuring that agriculture is protected through providing the farmers with adequate security measures that are environmentally friendly. The future plans are based on increasing scalability and sustainability through use of satellite data, multimodal sensing and community-based warning systems. Revolutionary power of AI-IoT. This article discusses the methods through which smart farming and human-wildlife conflicts can be reduced.*

Key Words: *Internet of Things (IoT), Artificial Intelligence (AI), Hybrid CNN-Transformer architecture, Temporal Monitoring, AI-IoT system.*

I.INTRODUCTION

Small-scale farming is still an essential part of food security and economy in many parts of the world; nevertheless, repeated destruction of crops by wild animals such as deer, monkeys, boars, and elephants results in heavy financial loss and food insecurity. Traditionally, methods like using fences, human guarding, and ditch systems are costly and ecologically unsustainable, emphasizing the need for innovative automated and intelligent agricultural defense systems. Combining Artificial Intelligence (AI) and Internet of Things (IoT) is a milestone in moving towards boundary surveillance, but many perception challenges persist in night-time attacks of animals, where poor illumination conditions, motion blur, and cluttered background limit single-stage visual detectors, causing high rates of false positives and missed detections. In response to these challenges, we propose a novel, multi-step AI–IoT framework for efficient night-time wildlife detection and automated reaction. This solution includes frame stabilization, zero-reference curve estimation to enhance low-light brightness, and residual denoising as part of the pre-conditioning process for the feedstock, and a unique hybrid CNN-Transformer detector to detect spatial features, a second level cascaded verifier to minimize false alarms, and temporal multi-object tracking to sustain identity. Leveraging an edge-first processing system coupled with IoT devices, such as autonomous drones, targeted audio-based deterrent measures, and instant alerts to one's phone, the proposed solution creates a strong, future-proof solution to species identification and preventive deterrent application.

II. LITERATURE SURVEY

Zhang et al. [1] analyzed how the architecture evolved from CNN-based to Vision Transformer-based after analyzing various object detection techniques, stating that while attention had previously been on the local feature extraction process through CNN, it was now focused on global context extraction using Vision Transformers such as DETR and Swin Transformer, especially effective in chaotic environments. Li and Chen [2] compared single-stage (YOLO), two-stage (Faster R-CNN), and transformer-based detection methods, concluding that multi-stage models effectively achieved a good balance between recall and precision due to their combination of lightweight single-stage models with additional verification stages. Kumar et al. [3] built on the Small, Low-Contrast, and Partially Obscured Targets research by showing the efficacy of single-stage detectors in real-time wildlife monitoring, especially at night time, comparing YOLO variants on a range of test targets.

Moving from observation to action, Singh and Patel [4] have considered the use of IoT solutions in precision farming, laying down the groundwork for sensor networks and automation to improve farm security against animal intrusion. As part of a detailed review, Hernandez et al.[5] have pointed out the application of AI and IoT in smart agriculture, which can be stated that the use of edge computing reduces the use of bandwidths and makes real-time processing possible in rural areas having low connectivity, making the combination of both technologies effective in such locations. Besides the above infrastructure components, Gupta and Sharma [6] have provided an overview of IoT-based agricultural systems that include drones, sensor networks, and automatic actuators.

Because of the expensive deployment of edge enhancement methods on real edges, Wang et al [7] provided a thorough analysis of the currently available methods of low light enhancement and found out that the unsupervised zero-reference curve estimation techniques such as ZDC are more suited for use on real edges since they do not need a pair training method to normalize dynamic range. In order to justify the above assertion, Zhao and Lin [8] evaluated the curve estimation methods where the images were non-pairly illuminated using the non-reference method followed by object detection; it was discovered that enhancing illumination without reference reduced false positive.

In order to overcome the problem of platform instability under outdoor conditions, Chen et al. [9] have analyzed the effectiveness of a hybrid video stabilization algorithm which combines IMU sensors' data along with the optical appearance tracking results (for example, KLT) and shown that the stabilization process based on the sensors' data helps to reduce the rolling shutter effects and vibrations. Park and Lee [10] have studied deep learning approaches for video stabilization that take into account gyroscopic data and found that the video stabilization process contributes to improving spatio-temporal coherence and reduces false alarms due to camera motion. In order to overcome the issue of high-density sensor noise at distant scenes, Ahmed et al. [11] have compared several CNN-based video denoisers such as ViDeNN and FastDVDnet with respect to conventional spatial-temporal filters, namely, Non-Local Means, and revealed that light-weighted CNN-based video denoisers were able to preserve the complicated structure edges and maintain high efficiency.

Finally, the maintenance of target consistency for continuous video streams requires effective tracking algorithms. Zhang et al. [13, 14] have looked at the MOT systems of today and found that the addition of the Appearance Feature Link (AFLink) and Gaussian-smoothed Interpolation (GSI) modules to StrongSORT greatly helps to eliminate ID switches and false trajectory detection in situations where there is partial occlusion and varying lighting conditions. In order to conduct an analysis of these multi-stage pipelines, Brown et al. [15] have studied detailed verification procedures. They found that the combination of spatial detection metrics (mAP) and temporal tracking metrics (IDF1 score and ID switches) provides an effective benchmark.

III.METHODOLOGY

The proposed animal intrusion detection scheme integrates hardware-driven events, computer vision techniques, dynamic lighting systems, and cloud telemetry data. Rather than having the processing resources consumed by the computer vision algorithms running continuously, the system operates in an energy-saving idle mode until a boundary event takes place. The entire operation process is divided into five major stages, as illustrated below.

A. System Architecture and Initialization

The hardware system is orchestrated using a single board computer (SBC), Raspberry Pi 5 model. The peripheral components comprise of the optical laser-Light Dependent Resistor (LDR) beam barrier, BH1750 digital light sensor, optocoupler relay-controlled high-wattage spotlight, external sound system, HD USB Camera, and real-time ThingSpeak IoT cloud service connection. At boot time, the single board computer configures GPIO registers, peripheral interfaces (for ambient light detection using I2C and image acquisition using V4L2 interface), and imports the pre-trained YOLOv8 nano object detection model into the memory. The laser transmitter is kept always on to produce a focused beam over the surveillance site and falls on the LDR sensor receiver to form the optical loop. Operational hyperparameters consist of low-light threshold (τlux = 20lx), video subsampling frequency, sound alarm patterns, ThingSpeak API write key, and target animal filters (Bos taurus, Elephas maximus, and Ursidae).

B. Event-Driven Sensing and Image Acquisition

The vision process flow remains disabled for lower computational burden and energy consumption during baseline operations. The perimeter monitoring relies exclusively on the digital output signal of the optical barrier subsystem:Relay Control = {0 (Baselined), Beam Impact 1 (Enabled), Beam interrupted (1)}During the presence of an actual object near the boundary line, the digital output of LDR changes its state, causing hardware interrupts on the SBC. The system shifts to the enabled state when that change takes place. Camera Operation: The USB camera streams video frames at the default resolution of 640 × 480 pixels. Temporal Frame Thinning: In order to maintain the balance between the real-time analysis performance and processing efficiency, a thinning factor N = 3 has been adopted. Each N-th collected frame (Fk, k mod 3 = 0) is delivered to the detection module, reducing computational demand by about 66.7%.

C. Adaptive Illumination Control

Simultaneously with frame acquisition, the SBC queries the BH1750 ambient light sensor via the I2C protocol. The digital sensor quantifies illuminance (L) in lux. Dynamic light compensation operates according to the following control logic:

$$\text{Relay Control} = \{(\text{HIGH(Lamp ON)}, L < \tau\_\text{lux} \quad \text{LOW(Lamp OFF)}, L\ \tau\_\text{lux} \quad (2)$$

If low ambient light is detected (L < 20 lx), the relay energizes the auxiliary illumination system to illuminate the target area, ensuring adequate signal-to-noise ratios in incoming frames for downstream vision processing.

D. YOLOv8 Deep-Learning Object Detection and Localization

Subsampled frames are processed using the lightweight YOLOv8 Nano architecture optimized for edge devices. For each candidate frame F_k, the model executes bounding box regression and multi-class confidence scoring across target vectors:

$$\hat{y} = [\ b_x,\ b_y,\ b_w,\ b_h,\ p_c,\ C_1,\ C_2,\ \dots,\ C_m\ ] \qquad (3)$$

Where (b_x, b_y, b_w, b_h) represent bounding box center coordinates and dimensions, p_c is objectness confidence, and C_m denotes conditional class probabilities.

- **Filtering:** Model outputs are strictly filtered for three designated target classes: Cow, Elephant, and Bear. Non-target object detections are discarded to prevent false alarms.
- **Visualization:** For confirmed targets exceeding the class confidence threshold (τ_conf), bounding boxes, class labels, and probability scores are rendered onto the local frame display.

E. Alarm Actuation, IoT Telemetry, and System Rearmament

When a target class is positively identified, the SBC triggers local deterrence and remote logging mechanisms concurrently:

1. Local Deterrence: An audio alarm signal is routed through the 3.5mm AUX channel and played using the low-latency mpg123 media process. If no target animal is detected in the subsequent frames, the sound process is terminated.

2. Cloud Telemetry: System state variables and metric payloads are transmitted via HTTP POST requests to the ThingSpeak IoT platform. The multi-field JSON telemetry structure includes:

Fields 1–3: Target Class Presence Binary Flags (Cow, Elephant, Bear $\in \{0, 1\}$)
Field 4: Measured Ambient Light Level (L in Lux)
Field 5: Relay State (Lamp ON = 1, Lamp OFF = 0)
Field 6: Maximum Detection Confidence Score (max(p_c))

By coupling an asynchronous optical break-beam mechanism with a YOLOv8-based deep learning vision engine and ThingSpeak cloud telemetry, the design delivers an energy-efficient edge intrusion detection system. The event-driven processing paradigm selectively activates inference routines upon optical disruption, thereby significantly lowering continuous CPU utilization without compromising real-time detection accuracy.

F. System Flow Diagram

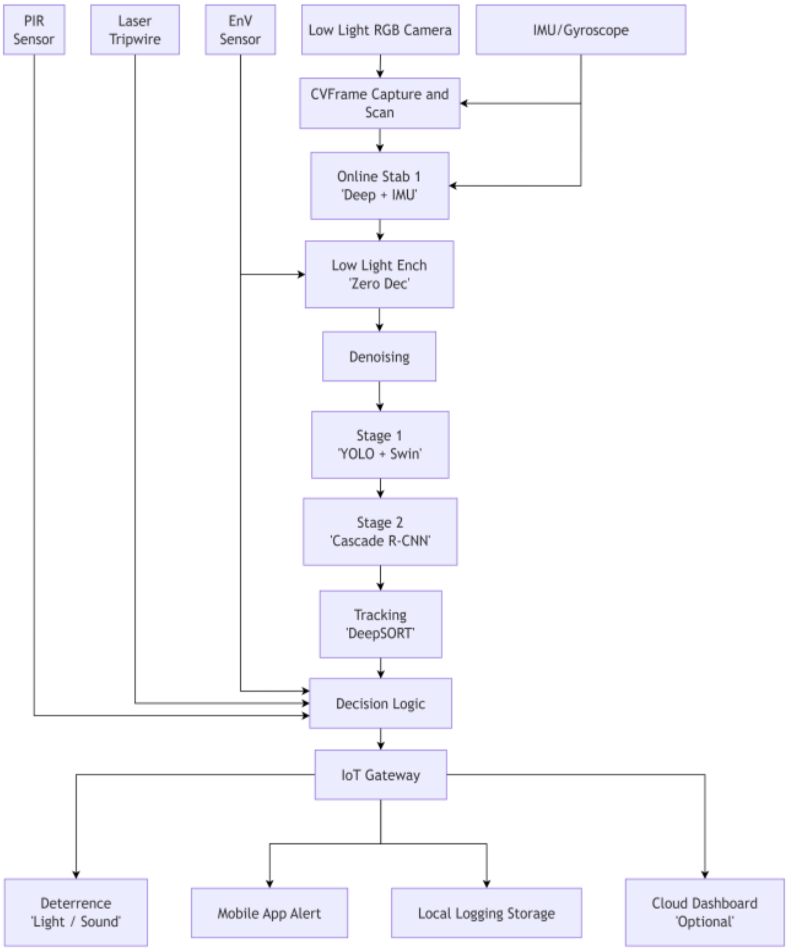

Fig. 1. Flow Chart of Proposed System

IV.RESULTS AND DISCUSSION

The proposed intelligent animal detection and monitoring system was experimentally evaluated using multiple animal images representing different species, including an elephant, cow, and bear. The vision module successfully detected and classified each animal in real time using the trained deep learning model. The detected object was enclosed within a bounding box, and the corresponding confidence score was displayed on the graphical user interface (GUI).

A. Animal Detection Performance

Figure 2 illustrates the successful detection of an elephant with a confidence score of 0.86. The detection model accurately localized the animal and generated the corresponding class label. Once the elephant was detected, the system entered the animal detection mode and prepared the laser trigger mechanism.

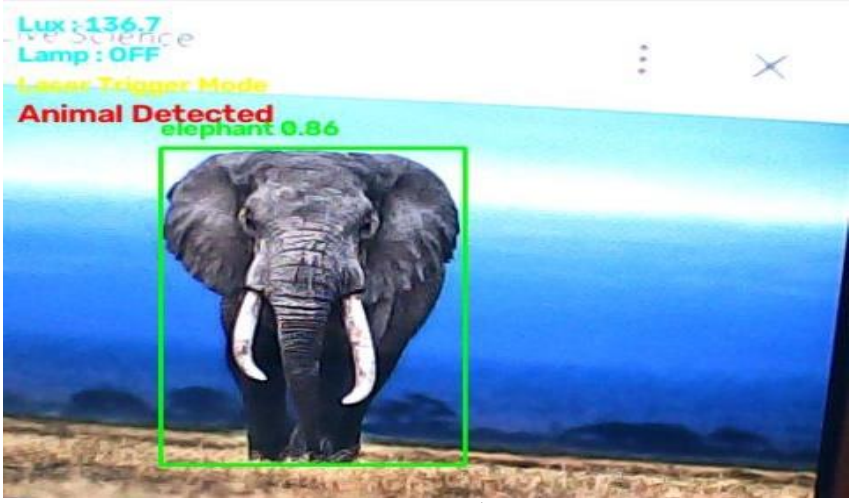

Fig. 2. Elephant Detection of Proposed System

Fig. 3. Bear Detection of Proposed System

Figure 3 shows the detection of a bear with a confidence score of 0.96, which represents the highest confidence among the tested samples. The result indicates that the trained model can accurately distinguish different animal species under varying image conditions.

Similarly, Figure 4 presents the successful detection of a cow with a confidence score of 0.88. The bounding box correctly enclosed the entire animal without false detection, demonstrating the robustness of the object detection algorithm

Fig. 4. Cow Detection of Proposed System

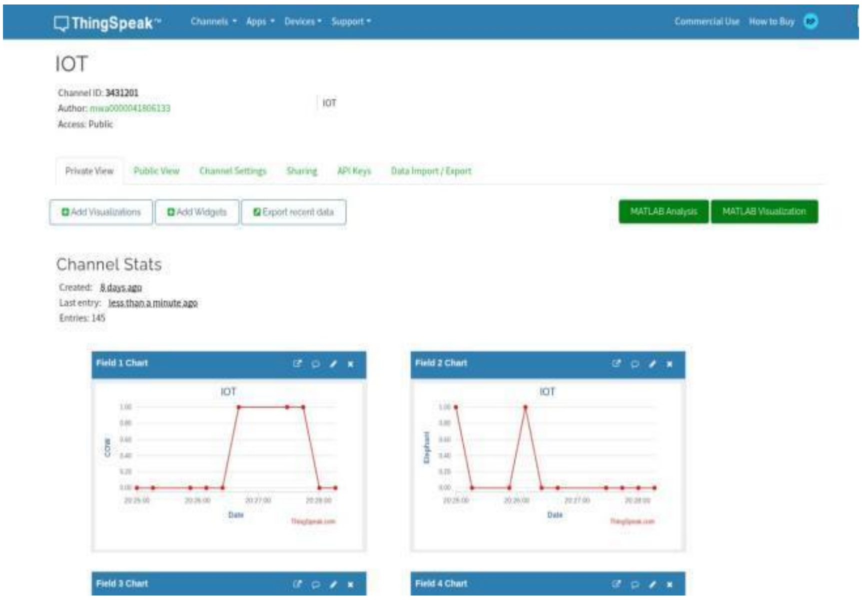

Fig. 5. IoT Platform of Proposed System

Figure 5 shows the ThingSpeak cloud channel overview illustrating real-time data logging and continuous telemetry for specific animal classifications, including binary detection events for cows and elephants.

Figure 6 illustrates the ThingSpeak cloud dashboard depicting secondary detection parameter streams, including bear intrusion events, real-time GPS coordinate updates, and deterrence activation statuses (lamp actuation).

The experimental results demonstrate that the proposed detection model provides reliable real-time performance with confidence scores ranging from 86% to 96%.

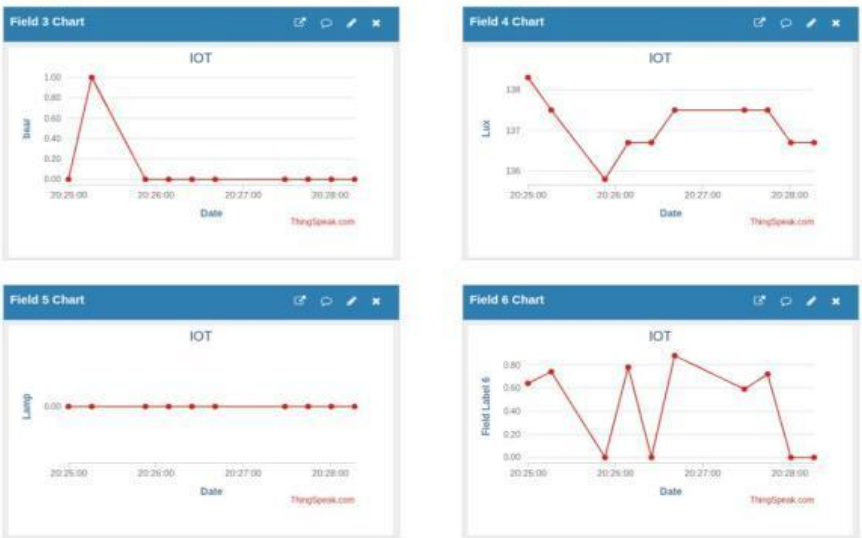

Fig. 6. IoT Results of Proposed System

B. Sensor Monitoring

The ambient light sensor continuously measured the surrounding illumination level during system operation. The measured lux values varied between 136.7 lx and 138.3 lx, indicating stable environmental lighting conditions throughout the experiment.

The GUI continuously displayed:

- Ambient Light (Lux)
- Lamp Status
- Laser Trigger Mode
- Animal Detection Status

This real-time visualization enables operators to monitor the system without additional diagnostic tools.

C. IoT Data Transmission

The detected animal information and sensor measurements were successfully transmitted to the ThingSpeak cloud platform through the IoT communication module.Whenever a specific animal was detected, the corresponding ThingSpeak field changed from 0 to 1, confirming successful event transmission. Sensor values and confidence scores were simultaneously updated in real time.

The cloud dashboard successfully recorded 145 data entries, demonstrating reliable communication between the embedded system and the cloud server without noticeable packet loss.

V.CONCLUSION

The results of the experiment prove the efficiency of combining computer vision, IoT communication, and environmental sensors into one system through the proposed intelligent surveillance system. It can be claimed that the object detection algorithm showed high-confidence levels (from 0.86 to 0.96) regarding various types of animals; therefore, good results can be expected from classification. The detection part and the ThingSpeak cloud were synchronized in real time, which means that the wireless communication system was reliable. Moreover, ambient light detection helps use the deterrent laser device depending on the environment. The proposed system is suitable for different purposes, including crop protection, wildlife studies, forest management, and intelligent agriculture.

VI.ADVANTAGES

• Robust Nocturnal Detection

Through the incorporation of low-light image enhancement, deep video denoising, and dynamic stabilization, the multi-stage preprocessing technique ensures consistent reliability within the night-time adversarial scenario, effectively minimizing the number of false positives caused by motion blur or lens glare.

• High Precision Through Multi-Stage Verification

The vision pipeline is built upon the use of the fast one-stage model to perform preliminary detections, which is then verified by the powerful detector (Swin Transformer / Cascade R-CNN). This two-step process helps avoid false positives as well as solve the issue of overlapping bounding boxes in an agro-based cluttered environment.

• Temporal Consistency and Reduced False Alarms

Multi-object detection algorithms (DeepSORT/StrongSORT) are employed to ensure consistency over consecutive frames. Removing transient bursts and spurious detections provides stable tracking, hence boosting trust in automatic alerts from the users' side.

• Edge-First Deployment for Real-Time Response

The proposed edge-oriented architecture facilitates high frame rate processing (Appro. 30FPS) within the field node itself. By offloading the task from cloud servers, no latency exists, guaranteeing operation in areas where bandwidth is lacking, such as in the rural areas.

• Eco-Friendly Deterrence Mechanisms

This technology sets off humane deterrents like focused beams of light and varied audio frequencies that help achieve peaceful co-existence between man and beast without employing controversial techniques such as electrification or electric barriers.

• Scalability and Adaptability

It has been designed using a modular architecture that scales very well for different wildlife and geographic locations. It incorporates quantization and lightweight models in order to cater to low-resource farms.

• Comprehensive Evaluation Protocol

The approach has been thoroughly benchmarked using conventional metrics for evaluation of detection and tracking (mAP50-90, ID Switches, false alarm rate, and FPS). Detailed ablation experiments substantiate the incremental benefits introduced by the respective preprocessing and verification steps.

• Insights and Logging

Constant logging of metadata such as species identification, accuracy of the bounding boxes, and logs on time of appearance helps in analyzing the process and improving the threshold settings.

VII.FUTURE SCOPE

Future endeavors will focus on building robustness using multisensor fusion with acoustic sensors, thermal sensors, and velocity sensors, in addition to vision systems, to improve recognition of different species in complex environments outside. To increase scalability, our goal will be to use adaptive and lightweight edge-based systems which allow continuous learning in different environmental settings of wildlife. In addition, integrating both terrestrial Internet of Things sensors and drones for aerial surveillance will improve border coverage. Finally, extending the framework for multiple crop pests and community-based projects will provide a more sustainable agriculture protection system ethically.

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