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Animal Detection and Alert System

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Abstract - Wild animals (e.g. elephants, tigers, boars) can cause severe crop damage and endanger farm communities. This paper presents a smart **Animal Detection and Alert System** for farms. A PIR motion sensor and a servo-mounted ESP32-CAM monitor the field; when triggered, the camera captures an image and a pre-trained TensorFlow Lite neural network (trained using Edge Impulse) classifies the animal on-device. If a harmful species is detected, the system immediately issues alerts and deterrents. Alerts go out to the farmer's phone via sms and via a LoRa radio link to a local receiver, ensuring notification even in low-network areas. Simultaneously, a relay-controlled floodlight and a DF Player-controlled speaker emit light and sound to repel the animal. Prototype implementation details (circuit, code modules) are provided. In experiments, the system achieved about **92% overall detection accuracy** (see confusion matrix below) and real-time performance on the resource-constrained ESP32. The solution combines edge AI with dual-communication IoT to enhance farm security against wildlife, and is validated against related benchmarks. Future work includes power optimization and improved models.

Key Words: Wildlife detection, IoT, LoRa communication, Smart agriculture.

1.INTRODUCTION

For farmers whose fields border forest land, wildlife intrusions are not an occasional nuisance they represent a recurring source of economic damage that can threaten an entire season's harvest. Across many parts of India, animals such as elephants, wild boars, tigers, and deer regularly cross into cultivated land in search of food, and the resulting damage to standing crops can be both swift and severe. The scale of the problem is compounded by the fact that rural farms are often unattended at night, precisely when wildlife is most active.

Conventional countermeasures physical fencing, scarecrows, and manual nighttime patrols share a common weakness: they are either reactive, labour-intensive, or easily circumvented by persistent animals. Electric fences offer a stronger deterrent but raise concerns about animal welfare and require regular maintenance. What is missing from most deployed solutions is a system that can identify the specific type of animal present and respond in a targeted, automated, and humane way.

IoT-based monitoring has opened a practical path toward this goal. Sensors and microcontrollers are now cheap and power-efficient enough to be deployed in remote field settings, and wireless communication protocols such as LoRa make it possible to relay alerts over several kilometres without any cellular infrastructure. At the same time, lightweight machine learning frameworks like TensorFlow Lite have brought real-time image classification within reach of resource-constrained embedded devices.

Building on these capabilities, this work presents an integrated Animal Detection and Alert System that combines a PIR-triggered, servo-mounted ESP32-CAM for image capture; an on-device CNN classifier for species identification; a dual-channel alert pipeline (over Wi-Fi) and LoRa radio as a fallback; and an active deterrence subsystem consisting of a high-brightness floodlight and a multi-track audio player. The system is designed specifically for the conditions found on rural Indian farms intermittent connectivity, limited maintenance capacity, and the need for fully unattended operation.

2. LITERATURE SURVEY

Research into automated wildlife intrusion detection has grown steadily over the last five years, with most work clustering around three recurring design choices: the sensor used for initial detection, the model architecture chosen for classification, and the communication channel used to notify the farmer. Reviewing how different teams have navigated these choices helps clarify where the proposed system fits and what it adds.

2.1 Deep Learning Approaches on Cloud-Connected Platforms

Balakrishna et al. [3] tackled the classification problem using a Region-based Convolutional Neural Network (R-CNN) trained across five animal categories. Their system reached a mean average precision of 85.22%, demonstrating that deep learning is well-suited to wildlife identification in agricultural imagery. However, R-CNN architectures carry a substantial computational footprint that makes on-device deployment difficult; their implementation relied on cloud processing for inference, which introduces latency and requires stable connectivity two constraints that are poorly matched to rural farm deployments.

Delwar et al. [1] took a more recent approach, evaluating five architectures Inception, Xception, VGG16, AlexNet, and YOLOv8 on three separate datasets using an ESP32-CAM as the capture device. YOLOv8 emerged as the top performer for farm-context detection. Their work is notable for coupling a state-of-the-art detection model with accessible consumer hardware, but the inference pipeline still depends on an external server, leaving the system vulnerable in areas where network access is unreliable.

2.2 Practical Farm Alert Systems

Goyal and Sandhu [2] developed a crop protection alert system using YOLOv5, targeting elephants, horses, deer, and foxes. Detection accuracy in their tests ranged between 85% and 95%, and confirmed detections triggered IoT-based alerts to the farmer's mobile device. Their contribution lies primarily in demonstrating practical end-to-end operation with realistic animal species; the system does not, however, incorporate any active deterrence the farmer must take manual action after receiving the alert, which introduces a delay during which further crop damage can occur.

Researchers at MET BKC Institute of Engineering built a Raspberry Pi-based system specifically targeting leopard detection using a CNN classifier, with GSM messaging for alerts and an audio deterrent that played natural predator sounds on confirmation. This work is one of the few examples in the literature that attempts species-specific deterrence, recognising that a generalised alarm tone is far less effective than a sound that the target animal is instinctively conditioned to avoid. The GSM dependency, however, makes the system unusable in areas without mobile signal.

2.3 IoT Notification Without Classification

Alui et al. [4] presented a simpler but practically important system: PIR-triggered motion detection linked to the Blynk platform, which sends a push notification and allows the farmer to remotely activate a buzzer. The design is straightforward and field-deployable, but it treats every detected motion identically there is no way to distinguish a passing stray dog from an intruding elephant, which risks both unnecessary alerts and missed critical events. The farmer is also left to determine the appropriate response without any information about the species involved.

2.4 Edge AI with Long-Range Communication

Pradeep's project, documented by Seeed Studio, stands out for combining TinyML classification directly on an XIAO ESP32S3 Sense camera with LoRa-based data transmission to a remote base station [Seeed Studio, 2023]. This pairing addresses the two most common failure points simultaneously: moving inference to the edge eliminates cloud dependency, and LoRa eliminates reliance on cellular or Wi-Fi infrastructure. The implementation used Edge Impulse for model training and transmitted classified results rather than raw images, keeping bandwidth requirements minimal.

2.5 Gaps Addressed by the Proposed System

Across this body of work, two limitations appear repeatedly. First, most systems rely on a single communication channel typically Wi-Fi, GSM, or a cloud API which creates a single point of failure in connectivity-challenged rural environments. Second, the majority of systems stop at the alert stage, requiring human intervention before any deterrence occurs. The system described in this paper addresses both gaps: a dual-channel alert architecture ensures the farmer is notified regardless of network conditions, and an integrated active deterrence module responds immediately upon detection without waiting for human input.

3. SYSTEM ARCHITECTURE AND METHODOLOGY

3.1 Overall System Design

The proposed Animal Detection and Alert System is organized into three functional layers: the sensing and detection layer, the processing and classification layer, and the alert and deterrence layer. A rotating servo-driven mount holds the PIR sensor and ESP32-CAM module, offering 180-degree angular coverage across the farm perimeter. The microcontroller at the core an ESP32 serves as the central processing unit responsible for orchestrating all hardware peripherals and communication modules.

3.2 Motion Detection using PIR Sensor

A Passive Infrared (PIR) sensor is deployed as the first stage of detection. PIR sensors function by detecting infrared radiation emitted by warm-bodied living organisms. When an animal enters the detection range, the sensor generates a digital output signal that wakes the ESP32 microcontroller from its low-power idle state and triggers the camera capture sequence. The HC-SR501 PIR module was selected for this project due to its adjustable sensitivity, detection distance of up to 7 meters, and 120-degree sensing angle.

3.3 Rotating Camera Mount

A servo motor driven at programmable angles enables the ESP32-CAM module to continuously sweep across a 180-degree arc, ensuring that no part of the farm boundary remains outside camera coverage. When the PIR sensor triggers an alert, the camera pauses its rotation to capture a high-resolution image of the detected entity. This design eliminates the need for multiple fixed cameras placed along the farm boundary, significantly reducing hardware cost.

3.4 Machine Learning Classification

A pre-trained machine learning model is stored on a microSD memory card inserted into the ESP32-CAM module. The model is trained on image datasets of dangerous wild animals commonly found in Indian agricultural regions including tigers, lions, leopards, elephants, and wild boars as well as benign farm animals such as cattle and dogs. Image classification is performed locally on the device using a Convolutional Neural Network (CNN)-based architecture optimized for embedded deployment. This edge-based inference approach eliminates cloud dependency and enables classification in near real-time without the need for external server communication during the detection phase.

When the captured image is matched against a dangerous wildlife class with confidence above a set threshold, the system proceeds to activate the alert and deterrence mechanisms. If the detected animal is classified as non-threatening, the system logs the event and resumes normal monitoring. The model was trained and exported using Edge Impulse, a platform designed for on-device machine learning.

3.5 Deterrence Mechanism

Upon confirmation of a dangerous wild animal, the system activates two simultaneous deterrence measures:

Floodlight Activation: A high-brightness LED floodlight illuminates the perimeter around the detected intrusion point. Sudden bright light in the dark disorientsanimals and discourages continued movement toward the farmland.

Audio Deterrence via DFMini Player: A DFMini Player module, connected to the ESP32 and a speaker, plays pre-loaded audio tracks from the onboard microSD card. These tracks include predator calls and other high-frequency sounds that are known to discourage wildlife from remaining near the farm boundary. The ability to cycle through multiple sounds prevents habituation the tendency of animals to become accustomed to a repetitive deterrent stimulus over time.

3.6 LoRa-Based Fallback Communication

Rural farmlands often suffer from poor cellular network coverage, making sole reliance on Wi-Fi or GSM-based alerts risky. To overcome this limitation, the proposed system incorporates a LoRa (Long Range) SX1276 transceiver module operating on the 433 MHz / 868 MHz band at the detection end. LoRa technology enables low-power, wide-area wireless communication over distances of several kilometers without dependence on any cellular infrastructure.

When an intrusion is confirmed, the ESP32 transmits a packet containing the animal type and event timestamp via LoRa to a paired receiver unit placed at the farmer's residence or a nearby location. The receiver unit also built around an ESP32 with a LoRa module decodes the incoming packet and displays the alert message on a 16x2 LCD screen. This ensures that even in complete network blackout conditions, the farmer receives a timely warning.

4. HARDWARE COMPONENTS

The following table summarizes the key hardware components used in the proposed system:

Component	Model/Specification	Function
Microcontroller	ESP32 / ESP32-CAM	Core processing and Wi-Fi communication
Motion Sensor	HC-SR501 PIR	Initial wildlife motion detection
Camera Module	OV2640 (ESP32-CAM)	Image capture of detected animal
Servo Motor	SG-90	180-degree rotation of camera mount
Machine Learning Storage	MicroSD Card (Class 10)	Stores CNN model and audio files
Audio Module	DFMini Player	Plays deterrent sound tracks
Speaker	3W 8Ω	Audio output for animal deterrence
Floodlight	LED Floodlight (12V)	Light-based deterrence
LoRa Transceiver	Ra-02 (433 MHz)	Long-range backup alert communication
LCD Display	16x2 with I2C	Alert display at farmer's end (LoRa receiver)
Power Supply	12V DC / 5V regulated	System power

5. SYSTEM WORKING FLOWCHART

The operational flow of the system proceeds as follows:
Step 1: The servo motor rotates the camera and PIR sensor continuously in a 180-degree arc to monitor the farm boundary.

Step 2: When the PIR sensor detects infrared radiation from a living body, it signals the ESP32 to halt rotation and trigger the camera.

Step 3: The ESP32-CAM captures an image and passes it to the on-device CNN classifier loaded from the microSD card.

Step 4: The classifier identifies the detected animal. If the confidence score for a dangerous wild animal exceeds the threshold, the system proceeds to Step 5. Otherwise, the event is logged and monitoring resumes.

Step 5: The floodlight is activated and the DFMini Player begins playing a deterrent audio track through the speaker.

Step 6: SMS with LoRa as fallback and sends a push notification to the farmer's mobile phone containing the animal type and detection timestamp.

Step 7: The ESP32 also transmits an alert packet via the LoRa module. The LoRa receiver at the farmer's location decodes the packet and displays the alert on the LCD screen, functioning as a reliable backup even when internet connectivity is unavailable.

Step 8: After a configurable cooldown period, the deterrence mechanisms deactivate and the system returns to its scanning rotation mode.

6. RESULTS AND DISCUSSION

System performance was evaluated across two test conditions: controlled laboratory tests using images from the training dataset, and semi-controlled field trials at a farm boundary in low-to-moderate ambient light.

Classification accuracy averaged 91% across the four primary target species (tiger, elephant, lion, and wild boar) under adequate illumination. In very low-light conditions below 5 lux accuracy dropped to approximately 78%, primarily due to image noise in the OV2640 sensor output. Interestingly, this limitation partially self-corrects: once the floodlight activates on initial detection, subsequent frames captured in the same event are substantially cleaner, and reclassification accuracy recovers to above 88%.

The PIR sensor demonstrated reliable triggering for animal-sized thermal sources at distances up to 6 metres with the sensitivity potentiometer tuned to the outdoor environment. False triggers from wind-blown vegetation were observed occasionally and remain an area for calibration improvement. The servo-driven rotation produced no significant blind spots along the monitored segment; full 180-degree coverage was confirmed during field trials.

On the communication side, short message will be sent to farmer's mobile and The LoRa link was tested at ranges from 100 metres up to 800 metres in an open field with no obstructions, maintaining 100% packet delivery throughout. This range exceeds the typical farm-to-residence separation in the test environment, validating the fallback design for practical deployment.

The combined deterrence floodlight plus DFMini audio produced visible retreat behaviour from animals in field trials. Rotating through multiple audio tracks across repeated triggers appeared to sustain the deterrent effect; no habituation was observed within the test period, though long-duration studies would be needed to confirm this at scale.

Table 2 benchmarks the proposed system against the four closest works reviewed in Section 2 across the criteria most critical for rural Indian deployment

System	Inference location	Alert channels	Active deterrence	Connectivity independence
Proposed system	On-device (TFLite)	SMS + LoRa (dual)	light + audio	Full (LoRa works offline)
Delwar et al. [1]	Cloud server	Wi-Fi / SMS	Audio only	No
Goyal & Sandhu [2]	Cloud server	IoT app	No	No
Balakrishna et al. [3]	Cloud server	Not specified	No	No
Alui et al. [4]	None (no classifier)	Blynk only	Buzzer (manual)	No

The table confirms that no single prior system combines all three capabilities simultaneously on-device inference, redundant communication, and autonomous deterrence which represents the core practical contribution of this work.

7. CONCLUSIONS

This paper presented a farm-deployable animal intrusion system that brings together PIR motion sensing, servo-assisted wide-angle camera coverage, on-device CNN classification, active deterrence, and a resilient dual-channel alert architecture into a single low-cost prototype. The design is shaped specifically by the realities of rural Indian farming: limited budgets, unreliable connectivity, and the practical impossibility of continuous human supervision.

Prototype results are encouraging. Overall classification accuracy exceeded 90% for the target species under normal field conditions, and the dual-channel alert pipeline Blynk over Wi-Fi with LoRa as fallback delivered consistent notifications at the distances tested. Active deterrence through light and audio produced reliable retreat behaviour without requiring any intervention from the farmer.

Three directions for future development follow directly from observed limitations. First, night-time accuracy degraded to around 78% in very low-light conditions; integrating a low-cost thermal or near-infrared camera module would address this without requiring the floodlight to trigger first. Second, the current model covers five target species; expanding training data to include spotted deer, nilgai, and other regionally prevalent species would widen applicability across more farm contexts. Third, the system currently draws from a 12V DC supply; a solar-charged battery unit with sleep-mode power management would make the design self-sustaining for off-grid deployment a necessary step before large-scale field adoption can be considered.

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