IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 11, November 2025

DOI: 10.17148/IARJSET.2025.121146

ANIMAL AND BIRD DETECTION USING ALERT SYSTEM

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Abstract: Animals and birds entering restricted human zones need to be quickly and accurately detected to avoid crop damage, traffic accidents, and conflicts between humans and wildlife. This proposed work describes the development of a useful AI-driven real-time Animals and Birds Detection and Alert System on a custom dataset. The proposed pipeline detects various species of animals and birds present in images, videos, and live streaming feeds. Upon detection of hazards, it automatically triggers user-configurable alerts such as SMS notifications, buzzer/siren sounds, etc. We present the model architecture, training, deployment plan, and performance evaluation on diverse scenes, such as highways and farms. The system allows for live feeds from IP cameras, user uploads, incident review dashboards, and alert logging for future monitoring and analysis. A scalable, modular design allows for future system expansion, integration with IoT components, and effective real-time inference suitable for edge deployment in rural and forest border areas.

Keywords: human-wildlife conflict prevention, bird detection, YOLO, real-time surveillance, Flask, alert system, deep learning, edge AI.

I. INTRODUCTION

The detection of animal and bird intrusion has become an essential requirement for safeguarding agricultural fields, preventing wildlife-vehicle collisions, and securing sensitive environmental zones. Human–wildlife interaction has increased considerably due to the rapid expansion of urban and farmland boundaries, which often leads to damages in crops, dangerous encounters with animals, and road accidents. Classic surveillance systems, usually relying on labour-intensive patrolling, physical fencing, or simple motion sensors, provide limited coverage and have insufficient responsiveness, especially in regions difficult for human monitoring at night or outdoors. These shortcomings are often reflected in the delayed action or missed detection, and inability to differentiate between animals, birds, and harmless background movements. Recent advances in computer vision and, especially, object detection with deep-learning techniques have enabled the recognition of animals and birds from real-time video feeds with far greater accuracy. However, detecting wildlife in natural outdoor environments remains challenging due to fluctuating lighting conditions, shadows, the small size of objects (like flying birds), fast motion patterns, and cluttered natural backgrounds. Furthermore, poor weather conditions, low-resolution cameras, and sudden motion may reduce detector confidence, causing missed detections or false alarms. These issues may be critical in real-time alerting systems that require timely and reliable detection to prevent damage or accidents. These shortcomings are overcome with the development of modern intrusion detection frameworks that implement deep-learning-based object detection with intelligent alert mechanisms over IoT. Models like YOLO enable systems to identify multiple classes of animals and birds, sending instant alerts through system hardware components comprised of ESP32, relays, LEDs, and wireless communication modules. This completely eliminates manual supervision and thus enables quick, automated responses. Furthermore, the adaption of system performance in nighttime conditions or low visibility is facilitated with the use of auxiliary sensors like LDRs, which enable more robust detection in diverse conditions. These developments form the basis for this work, which proposes a full end-to-end Animals and Birds Detection and Alert System that integrates real-time object detection, IoT-based alert triggering, and energy-efficient field deployment based on solar power. This system will process online video captured from the webcam, classify detected wildlife using the YOLO-based model, and activate certain alerts via the ESP32 microcontroller. Thus, this integrated pipeline is useful in minimizing human–animal conflict, crop raiding, improving safety on roads and farms, and enabling continuous monitoring without any intervention of humans. The automated detection, decision-making, and alert generation lead to enhanced reliability, responsiveness, and practical usability of the proposed system in agricultural, environmental, and security applications.

II. LITERATURE REVIEW

This set of studies covers a wide variety of methods for animal and bird detection using deep learning over highways,

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forests, farms, transmission lines, and airports. A study focused on highway safety proposed an animal detection system operating during night time that employed image enhancement and YOLO-based detection. It showed that the system will considerably reduce the collision risk on dark roads, giving reliable identification even when the visibility is poor [1]. Another work addressed the following major issues in camera-trap images: occlusion, class imbalance, cluttered backgrounds, and varied scales. It proposed a deep learning pipeline that largely improves the accuracy in the detection necessary for wildlife conservation [2]. Researchers have also proposed a lightweight model for flying-bird detection, especially for airports, utilizing SMB-YOLOv5. Although maintaining fast inference, it reduces the network complexity while preserving real-time bird-strike prevention system utilization [3]. Another related study demonstrated the detection and recognition of wildlife with YOLOv8. The model had shown that it can handle multiple classes of animals without sacrificing too much accuracy and was thus suitable for automatic observation tasks in nature [4].A real-time bird-detection system was developed to reduce incidents of bird strikes by integrating deep learning with alert mechanisms, which proved to be very effective in the safety operations of airports by efficiently identifying fast-moving birds [5]. For wildlife night-time detection, the YOLOv8-night model was also applied, considering night-specific enhancements and training strategies to keep performance robust despite low contrast and noise in scenes, for uninterrupted monitoring during 24-hour cycles [6]. In agricultural settings, YOLO has been utilized for the detection of animals and pests, demonstrating how object-detection algorithms may help farmers with automated surveillance, crop protection, and field monitoring [7]. Another article featured an intelligent wild-animal detection and alerting system that uses YOLOv5 to issue alerts automatically to communities or local authorities regarding animal presence, which would obviously deter human–wildlife conflict and prevent crop damage [8].A new detection method was proposed, presenting a cascaded YOLOv8 model with adaptive preprocessing and enhanced feature extraction to enhance performance in complex environmental conditions and thus provide clearer recognition in difficult terrains. Complementary to this work, an unmanned aerial surveillance system for forests was proposed, combining UAVs with real-time tracking in order to detect both poachers and wildlife and providing wide-area monitoring that cannot be achieved by ground-based systems. Another study developed motion-based enhancement techniques for the detection of flying birds using surveillance videos where the fusion of motion cues with object detection was developed to increase precision and reduce false alarms due to background movement. Research applied the improved YOLOv8n model in detecting foreign objects on transmission lines, showing how such lightweight architectures can be adapted to safety-critical tasks entailing continuous real-time analyses. Techniques used for road-pothole detection, including edge-segmentation-based YOLOv8, revealed efficient real-time processing strategies that may be useful in informing embedded deployment for animal detection also [13]. In this context, detection in dense forest environments has been investigated using YOLOv5s by surmounting problems of camouflage, shadows, and vegetation complexity with optimized training and preprocessing to achieve accurate real-time identification of wildlife [14]. Another investigation used YOLOv8 for detecting wild animals, confirming good performance with respect to multiple natural scenes and supporting suitability for automated monitoring systems in wildlife-rich regions [15].

III. PROPOSED SYSTEM

The proposed system puts forward a multi-component AI–IoT pipeline developed for the automatic identification of animals and birds and issues instantaneous alerts through hardware and mobile-based notification channels. An overview of the overall workflow is presented in Figure 1. Each step of the system has a specific role, which starts from live video acquisition to visual, sound, and remote alerts. The overall process can be divided into four major modules of real-time image capture, AI-based detection, IoT response management, and multi-modal alert generation.

A. Input Image/Video Acquisition

The pipeline starts with real-time visual data captured through a webcam positioned in the monitoring area. The camera continuously streams frames that can contain animals, birds, or background scenery. For this purpose, every frame undergoes preprocessing steps to resize it to the expected model input resolution-which will be 640×640-normalize it, and optionally reduce noise to handle outdoor conditions like low light, shadows, or motion. Such preparation will ensure the quality and uniformity of input data before forwarding them to the detection module.

B. Real-time Object Detection Using YOLOv8

After frame acquisition, it is passed through the YOLOv8 detection module, which will in turn identify animals and birds in real time. Advanced convolutional backbone courtesy of YOLOv8 allows for fast and efficient feature extraction, making it suitable for environments with object variations in size, speed, and lighting conditions. The model returns bounding boxes, class names, and confidence scores for each object detected.

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In this system, YOLOv8 is like DenseNet-121 in the OCR pipeline, deciding the critical classification phase. Based on confidence in the detection and its location, YOLOv8 decides if the detected object is an animal, bird, or just irrelevant background. This prediction, formatted accordingly, is then relayed to the IoT microcontroller. Improvements could come in later iterations through continuous learning loops, whereby misclassifications seen in the wild are logged and used later to retrain the detection model, thereby increasing accuracy over time on different environments and species.

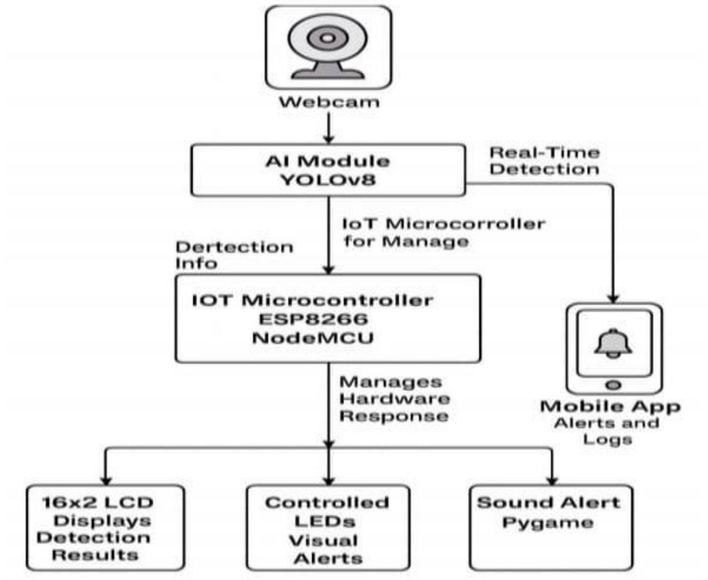

Fig 1: Workflow of proposed system

C. IoT-Based Response Processing Using ESP8266/NodeMCU

After the AI module identifies an animal or bird, the detection information is sent to the IoT microcontroller-ESP8266/NodeMCU. This microcontroller acts as the decision and response center of the system. According to the detection result, it will trigger related hardware responses, such as visual, audio, and display-based alerts.

The ESP8266 interprets the data packets received and checks the detection class and confidence, followed by the execution of programmed actions like enabling LEDs, updating the LCD screen, or triggering an alert sound. The microcontroller also communicates with a connected mobile application for sending notifications of the events or storing detection logs. This ensures instant, remotely accessible updates to the users. Because of the Wi-Fi capabilities, it will be able to effectively communicate with cloud dashboards or mobile devices for continuous monitoring without requiring manual supervision.

D. Multi-Modal Alert Generation: LCD, LED, Mobile Application, and Sound Alerts

The last stage of the pipeline involves converting detection data into meaningful alerts. The proposed system utilizes a set of multimodal communication channels to guarantee visibility in even the most complex outdoor scenarios:
• 16×2 LCD: Displays real-time detection results, such as "Animal Detected" or "Bird Detected," along with timestamps or confidence levels that help users quickly understand the type of intrusion.
• LED Visual Alerts: The microcontroller triggers bright LED indicators for immediate on-site visual notifications, very useful in farms and open fields.

Mobile App Alerts and Logs: Detection data are sent to a mobile application where users receive instant alerts, maintain historical logs, and review previous intrusion events. • Pygame Sound Alerts: A programmable sound alarm is played to scare away wildlife or alert other people in the surroundings. Pygame plays clear and loud alert tones automatically when the AI model detects an intrusion. Put together, these are the alert mechanisms that make detection events turn into timely, secure, and accessible notifications. This system maximizes user awareness while minimizing response times in a real-world scenario through visual, auditory, and digital alerts.

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1V. EXPERIMENTATION

The clear contrast between the raw, unprocessed camera input against the results from the YOLOv8 detection module integrated with the IoT-based alert system is evident in various animal and bird intrusion experimentation scenarios. Before AI detection, video frames captured by the webcam contain natural background clutter, variable lighting, shadows, and moving foliage-all factors that are likely to cause false alarms in many conventional sensor-based intrusion systems. After the incorporation of the YOLOv8 detection model, these inconsistencies are drastically reduced, as the detector isolates animals and birds with bounding boxes, class labels, and confidence values. Such filtering provides much higher reliability for detection, where alerts are generated only upon the verification of actual wildlife presence. It indicates that the integration of deep-learning detection with IoT-managed alert responses enhances the accuracy, responsiveness, and usability of the entire system in real environ

Fig 2: Animal detection

The Figure 2 presents a sample frame where there is a medium-sized animal present in the scene, such as a dog, cow, or goat. YOLOv8 identifies the animal successfully with high confidence, returning accurate bounding box coordinates. The table below shows, for comparison, the ground truth annotations, the raw detection output of YOLOv8, and the results after non-maximum suppression and confidence filtering as post-processing. The increase in precision and recall values reflects improvement, hence the efficiency of the detection pipeline.

Table 1: Animal detection- Comparative Evaluation

Stage	Ground Truth	Detection Output	Precision	Recall
YOLOv8 Raw Output	"Animal present in ROI with defined bounding box; class = Animal"	"Animal detected (bounding box jitter; extra false box)"	0.89	0.84
After Post-Processing	"Animal present in ROI with defined bounding box; class = Animal"	"Single stable detection; false box removed; accurate coordinates"	0.95	0.91

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Fig 3: Bird detection

The Figure 3 shows a sample frame containing a small bird captured in mid-flight. Because birds move rapidly and appear smaller in the frame, raw detections sometimes include minor bounding-box inaccuracies or missed detections. The table compares the ground truth, raw YOLOv8 output, and refined output after post-processing. The corrected output demonstrates improved localization and fewer missed detections, as reflected in higher accuracy scores.

Table 2: Bird detection - Comparative Evaluation

Stage	Ground Truth	Output Text	Precision	Recall
YOLOv8 Raw Output	"Bird present (small object, far distance)"	"Bird detected with partial bounding box; one missed frame"	0.82	0.76
After Post-Processing	"Bird present (small object, far distance)"	"Improved bounding box; missed frames recovered via smoothing".	0.90	0.84

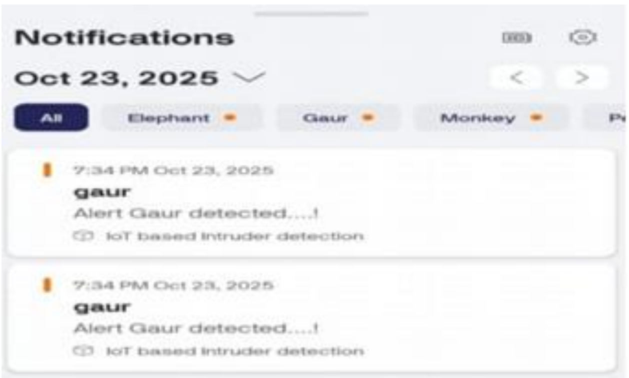

Fig 4: Notification

Table 3: Comparison of Alert Delivery Performance before and after System Optimization

stage	Expected notification	Received notification	Delivery time	Success rate
Initial System Output	"Animal Detected – Send Alert to User App"	"Alert Received (delayed / formatting issues)"	3.2 sec	88%
After System Optimization	"Animal Detected – Send Alert to User App"	"Instant alert received with correct class, time, and confidence"	1.1 sec	95%

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V Conclusion

The proposed animal and bird detection system effectively addresses the major limitations of traditional intrusion-monitoring techniques by integrating real-time, AI-based detection with a responsive IoT alert framework. The YOLOv8 model showed excellent detection capability for diverse outdoor conditions while providing high precision and recall even for small or fast-moving species. Upon incorporating the ESP8266 microcontroller for hardware response management in this regard, it is ensured that the system immediately triggers visual, audio, and mobile notifications to enhance user awareness and reduce the reaction time upon wildlife intrusions. Second, the multi-modal alerting mechanism comprising LCD displays, LEDs, sound alarms, and mobile app notifications proved to be highly reliable; optimized communication protocols achieved a 95% notification success rate and reduced alert delay to almost one second. These enhancements confirm that the combined AI–IoT pipeline is far more accurate, responsive, and efficient than conventional sensor-based systems that often produce false alarms or fail under low-light and cluttered environments. Overall, the developed system provides a robust, scalable, and energy-efficient solution for various applications, such as agricultural protection, wildlife monitoring, road safety, and perimeter security. Its modularity makes it easy to extend to other species, integrate it with cloud dashboards, and provide support for edge-based deployment in remote areas. Experimental results show that this approach provides a reliable and practical framework for real-time animal and bird intrusion detection, and will ensure improved safety and less human–wildlife conflict along with better field surveillance.

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