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PROTECTING CROPS FROM WILDLIFE ANIMALS IN SMART AGRICULTURE WITH REAL-TIME OBJECT DETECTION USING YOLOV5 ALGORITHM

Suresh **Maruthai**[1], Mageshwari **Munusamy**[2],
Prabakaran **Narayanaswamy**[3], Surendran **Rajendran**[4*]

[1]St Joseph's College of Engineering. Department of Electronics and Communication Engineering. Chennai, Tamil Nadu 600119, India.
[2]Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology. Department of Artificial Intelligence and Data Science. Chennai, Tamil Nadu 600055, India.
[3]Koneru Lakshmaiah Education Foundation, Department of Electronics and communication Engineering. Vaddeswaram, Andhra Pradesh 522501, India.
[4]Saveetha Institute of Medical and Technical Sciences. Saveetha School of Engineering, Department of Computer Science and Engineering. Chennai, Tamil Nadu 602105, India.
* Author for correspondence: surendran.phd.it@gmail.com

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ABSTRACT

Agriculture is essential for human survival, as it provides food, employment, economic growth, livelihood, and rural development, while also maintaining environmental balance and food security. However, due to the damage caused by wild animals, many farmers are abandoning cultivation. Existing techniques for deterring animals from agricultural fields are limited to their detection and the use of ultrasonic sounds. The proposed approach utilizes the YOLO machine learning algorithm to identify animals in the fields, generate ultrasonic sounds based on the detected species, activate Light-Emitting Diodes (LEDs) to simulate fire, and send an alert message to an authorized individual upon detection. The results obtained from this method surpass current approaches in reliability, precision, recall, and F1-score, achieving values ranging from 94 to 96 %.

Keywords: machine learning, animal deterrence, crop protection, food security.

INTRODUCTION

Agriculture is the science, skill, and practice of cultivating plants and rearing animals for food, energy, and other essential products that sustain human life. It encompasses a wide range of activities, from sowing and harvesting crops to managing livestock. Among the many challenges faced by agricultural systems, animal intrusion is a major source of losses. Wildlife such as deer, rabbits, and birds can damage crops by feeding on them, while larger animals, including cattle, horses, and even elephants, may trample plants and compact the soil. In addition, pests and diseases caused by insects, fungi, bacteria, viruses, and other pathogens can severely affect crops, leading to substantial yield losses (Mahaveerakannan, 2025). Extreme weather conditions, such as floods, frost, and hailstorms, further exacerbate these problems by destroying crops and disrupting agricultural cycles. Crop losses due to these combined factors represent a major challenge in agriculture, leading to significant financial setbacks and posing a serious threat to food security.

Over time, farmers have used a wide range of methods to protect their crops from animal damage, including electric fencing, scare tactics, chemical repellents, traps, and other deterrents. However, these traditional approaches present significant challenges. Electric fencing, although commonly used, can kill animals attempting to enter a field, raising ethical and ecological concerns. Chemical repellents, such as commercial sprays, urea, or homemade solutions, discourage animals through unpleasant tastes, odors, or irritation, but they may also pose health risks to humans who inhale contaminated air or consume treated produce, in severe cases leading to fatal outcomes. These limitations show the need for a smart, cost-effective, and eco-friendly solution capable of safeguarding crops without harming wildlife (Surendran *et al*., 2025).

In Bangladesh, rodents represent a major agricultural threat. While chemical rodent repellents are available, they can create health hazards for consumers. To address this, Awal *et al*. (2024) proposed an electronic rodent-repelling system that generates ultrasonic sounds when an intrusion is detected. For larger wildlife, such as deer, deterrence becomes more complex. Landform fluctuations can weaken echo signals, reducing the effectiveness of acoustic deterrence. To overcome this, Asada *et al*. (2024) developed a deer-repellent system using acoustic ray tracking and mountaineering algorithms, supported by OpenStreetMap data to better estimate deer locations.

Animal intrusion is not limited to agricultural fields, affecting roads, base camps, and rural communities as well. Despite the variety of available techniques, major advancements have been slow due to individual limitations of each method. As a result, recent studies have increasingly turned to artificial intelligence and image processing. Sajithra Varun and Nagarajan (2023) introduced deep learning techniques for early animal detection, using image prediction, classification, and feature extraction. Similarly, Fernando *et al*. (2023) applied deep learning algorithms to improve detection accuracy, while Dave *et al*. (2023) implemented YOLOv8 technology to enhance data extraction and precision, achieving superior results compared to earlier approaches. Arulprakash *et al*. (2025) contributed with a system validated at the field level using specific animal datasets, noting that future developments could scale the technology to larger farms, incorporate drone-based aerial monitoring, and adapt it to a broader range of species and environmental conditions.

Other researchers have examined species-specific challenges. Robertson *et al*. (2023) reviewed agricultural conflicts involving elephants across Asia and Africa and evaluated the effectiveness of semi-captive versus wild elephants. They also introduced a new repellent technology aimed at reducing crop damage. Raveena and Surendran (2024) addressed a different threat by studying *Amblyomma sculptum*, a South American tick species capable of transmitting pathogens, and proposed repellent strategies to reduce mosquito-borne disease transmission.

The escalating conflict between people and wildlife in agricultural landscapes has increased the need for advanced detection systems. Simla *et al*. (2023) introduced a deep learning algorithm combined with sensor monitoring to detect animals and send alerts to farmers and forest officers. Krishnamoorthy *et al*. (2024) showed that animals pose risks not only to crops but also to human safety; for example, snake bites cause approximately 120 000 deaths annually. To mitigate this, Punetha and Vuppu (2023) developed a snake-repellent model. Deforestation is another key driver of human-animal conflict that increases animal movement into farmlands. To address this, Natikar and Dayananda (2023) proposed an animal-recognition framework using Convolutional Neural Networks (CNNs) with TensorFlow Object Detection.

More recent work has advanced real-time intrusion detection. Delwar *et al*. (2025) evaluated several deep learning models and identified YOLOv8 as the most effective, reaching over 99 % accuracy. Their system was deployed on an ESP32-CAM IoT device to deliver real-time alerts. Likewise, Balakrishnan *et al*. (2025) developed a wildlife intrusion detection system using VGG16 with transfer learning and deep-SORT for real-time multi-animal tracking, achieving 92.19 % accuracy and automated alert delivery to support both crop protection and biodiversity conservation. Sonowal *et al*. (2025) proposed a low-cost Passive Infrared Sensor (PIR) classification method capable of distinguishing between humans and animals with 95 % accuracy, also providing estimates of intruder distance and movement direction.

Building on these advancements, the present work focuses on real-time image detection and deterrence of common wild and domestic animals. The proposed system integrates the You Only Look Once version 5 (YOLOv5) algorithm with Internet of Things (IoT) components, including Node Microcontroller Units (NodeMCU), Global System for Mobile Communication (GSM) modules, ultrasonic sensors, and LED indicators. The objectives were to (i) develop a real-time animal detection framework using image processing and deep learning; (ii) integrate deterrent mechanisms such as ultrasonic signals, LED lights, and GSM alerts; and (iii) evaluate system performance through experimental validation. It is hypothesized that combining YOLOv5-based detection with IoT-enabled deterrents will significantly improve crop protection, outperforming traditional classifiers such as Random Forest, CNNs, Support Vector Machines (SVMs), and Recurrent Neural Network (RNN) models in accuracy, precision, recall, and F1-score, offering a more effective and sustainable solution for preventing animal intrusions.

MATERIALS AND METHODS

Existing systems utilize an ARM Cortex microprocessor with edge Artificial Intelligence (AI) to detect animals through a camera and deter them accordingly. However, its functionality is limited to the deterrence of small animals. The proposed repellent system employs a NodeMCU (ESP8266) integrated with the YOLOv5 machine learning algorithm (Figure 1). In this system, animals are detected using a webcam.

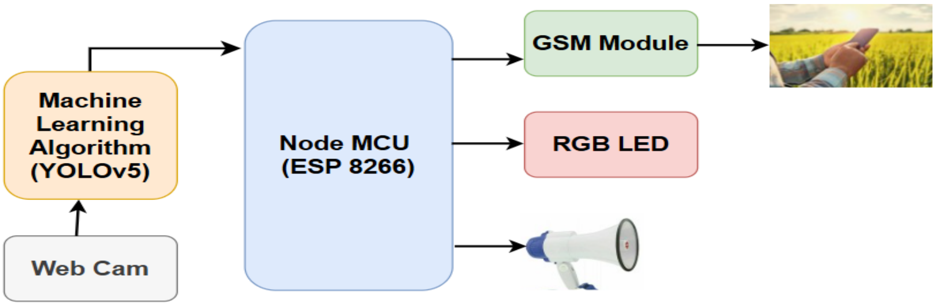

Figure 1. Proposed architecture of the smart animal repellent system with the YOLOv5 algorithm integrated with Node Microcontroller Units (NodeMCU), Global System for Mobile Communication (GSM) modules, ultrasonic sensors, and Light-Emitting Diodes (LEDs).

The camera captures images triggered by a PIR sensor with a detection range of 15–25 m. The captured images are then processed using the YOLOv5 algorithm for animal identification and deterrence.

Image dataset

In this study, a model was trained using a dataset comprising 5400 images of animals. These images were categorized into 90 different classes, including species such as bears, cattle, bulls, deer, butterflies, and peacocks. The dataset was obtained from Kaggle (https://www.kaggle.com/datasets/antoreepjana/animals-detection-images-dataset), providing a diverse range of animal images essential for the effective performance of the system. The dataset was divided into 70 % for training, 15 % for validation, and 15 % for testing. To enhance model robustness, data augmentation techniques such as flipping, rotation, and brightness adjustment were applied.

Image preprocessing

Implementing strategic landscaping practices, such as the cultivation of repellent plants, can alter the surrounding environment, making it less hospitable to wildlife and reducing the likelihood of animal intrusion. By integrating these diverse preprocessing and preventive methods, farmers can effectively mitigate crop damage and promote sustainable agricultural practices that prioritize the harmonious coexistence of humans and wildlife within shared ecosystems.

Before feeding images into the network, several preprocessing steps were used to enhance the performance and accuracy of the model. These include resizing the input images to a fixed size compatible with the network architecture and normalizing pixel values. Images were resized to a uniform dimension compatible with the model architecture (640 × 640 pixels for YOLOv5) to ensure consistent input representation and optimal model performance. The resizing operation is defined as:

$$I' = resize\big(I, (H, W)\big)$$

where, I is the original image, I' is the resized image, and H and W are the desired height and width, respectively.

Pixel values are normalized to a range that facilitates stable and efficient model training. Common normalization ranges include [0, 1] or [-1, 1]. The normalization operation can be expressed as:

$$p' = \frac{p}{255}$$

where p represents the original pixel intensity in the range [0,255]. This operation scales the pixel values to the range [0,1], standardizing the input data for the neural network.

YOLOv5 Algorithm

YOLOv5 is a state-of-the-art object detection algorithm that divides an input image into a grid and predicts bounding boxes along with class probabilities for objects within each grid cell. The algorithm is trained on annotated datasets containing images of animals with corresponding bounding boxes and class labels, and learns to recognize and differentiate animal species based on visual features such as shape, texture, and color.

YOLOv5 predicts bounding boxes using a grid-based structure, where each grid cell is responsible for predicting a fixed number of bounding boxes. The bounding box parameters are computed as follows:

$$b_x = \sigma(t_x) + c_x$$
$$b_y = \sigma(t_y) + c_y$$
$$b_w = p_w e^{t_w}$$
$$b_h = p_h e^{t_h}$$

where t_x and t_y represent the predicted center coordinates relative to the grid cell, while t_w and t_h denote the predicted width and height of the bounding box; (c_x, c_y) are the top-left coordinates of the corresponding grid cell, and p_w and p_h represent the anchor box dimensions. The sigmoid function σ constrains t_x and t_y to the range [0, 1], ensuring that the predicted center remains within the grid cell boundaries.

The YOLOv5 model was implemented using the PyTorch framework and trained for 200 epochs with a batch size of 16. The Adam optimizer was employed with a learning rate of 0.001. Training was performed on an NVIDIA RTX 2080 Ti GPU with 12 GB of memory and a system equipped with 32 GB of RAM. To accelerate convergence and enhance detection accuracy, pretrained YOLOv5 weights were utilized for transfer learning.

Each bounding box includes an objectness score, indicating the likelihood of containing an object. The objectness score is calculated as:

$$P_{object} = \sigma(t_0)$$

where t_0 is the raw objectness score predicted by the network.

YOLOv5 predicts the probability of each class for each bounding box. The class probabilities are determined as:

$$P_{class|object} = softmax(t_{class})$$

YOLOv5 utilizes a function that includes localization loss, confidence loss, and classification loss. The localization loss, which measures the error between predicted and actual bounding box coordinates, is defined as:

$$L_{loc} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} [(b_x - \hat{b}_x)^2 + (b_y - \hat{b}_y)^2 + ((b_w - \hat{b}_w)^2 + (b_h - \hat{b}_h)^2]$$

The confidence loss, which evaluates the accuracy of objectness predictions, is expressed as:

$$L_{conf} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} (C - \hat{C})^2 + \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{noobj} (C - \hat{C})^2$$

The classification loss, which quantifies the error in predicting object classes, is defined as:

$$L_{class} = \sum_{i=0}^{S^2} 1_{i}^{obj} \sum_{c \in classes} (p(c) - \hat{p}(c))^2$$

The total YOLOv5 loss function, which combines the above components, is represented as:

$$L_{total} = \lambda_{coord}L_{loc} + L_{conf} + \lambda_{class}L_{class}$$

where 1_{ij}^{obj} is the indicator function for the presence of an object, 1_{ij}^{noobj} is the indicator function for the absence of an object, S represents the grid size, B represents the number of bounding boxes per grid cell, and λ_{coord} and λ_{class} are hyperparameters to balance loss components, which collectively enable YOLOv5 to detect objects efficiently and accurately in real-time.

YOLOv5 identifies and classifies objects within images, as demonstrated by the bounding boxes around the animals (Figure 2). Each detected object is labeled with its corresponding class and confidence score, such as "monkey_0.53," "elephant_0.98," and "cattle_0.6, 0.88, 0.93, and 0.92," with the final classification determined by the highest confidence value. YOLOv5 is recognized for its speed and accuracy, making it suitable for diverse applications, including autonomous driving and security surveillance.

Figure 2. Example of object recognition and confidence labeling using YOLOv5.

The hearing frequency ranges of various animals were used for training (Table 1). Based on these frequency ranges, the system generates ultrasonic sounds for effective deterrence.

Table 1. Hearing frequency ranges of different animal species.

Animal	Frequency range (kHz)
Monkey	10–65
Elephant	12–16
Buffalo	3–40
Pig	40.5–42
Horse	33.5–55
Cattle	23–35

Experimental setup

After detecting and analyzing animals, the system executes three automated actions to deter intrusions (Figure 3). First, it emits ultrasonic sounds at species-specific frequencies to repel the detected animal. Second, it sends a Short Message Service (SMS) alert to the field owner through GSM module, which operates independently of internet connectivity. Third, it activates LED lights that flash with varying intensity to provide visual deterrence. The system integrates the YOLOv5 algorithm with the NodeMCU (ESP8266) microcontroller for a low-cost and efficient operation. The NodeMCU was programmed using Arduino Integrated Development Environment (IDE), while the machine learning model was developed in Python. The GSM module (SIM800) handled alert communication, and deterrent mechanisms were automatically triggered in real time based on the detection results.

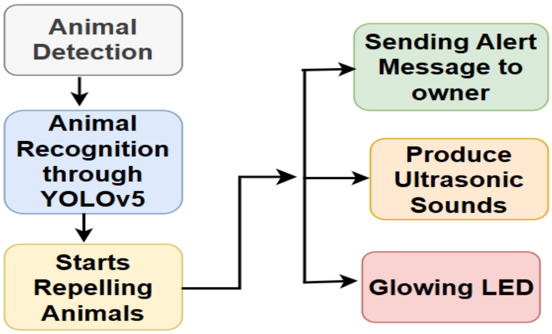

Figure 3. Process flow of the proposed animal detection and deterrence system.

In this study, the system utilized various hardware components, including the GSM module, ultrasonic sensors, LEDs, and the NodeMCU microcontroller, as well as software tools such as the Machine Learning Classifier, Python, and Arduino IDE (Table 2).

Evaluation metrics

Evaluation metrics play an important role in determining model performance through mathematical formulas. By analyzing these metrics, stakeholders can identify and select the most efficient system for wildlife deterrence. Accuracy is calculated as the ratio of the sum of True Positives (TP) and True Negatives (TN) to the total number of instances, including True Positives, True Negatives, False Positives (FP), and False Negatives (FN):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Table 2. Hardware and Software requirements of proposed system.

Hardware requirements	
Components	Specifications
Node microcontroller unit (ESP 8266)	-
Battery	5 V
Light-Emitting Diodes (LEDs)	2–3 V, 20 mA
Ultrasonic sensor (HC-SR04)	5 V; sensing distance of 2–400 cm
Global System for Mobile Communication (GSM) module (SIM800)	3.4–4.4 V; quad-band frequency
Passive Infrared Sensor (PIR)	5 V; sensing distance of 15–25 m
Software requirements	
Requirements	Purpose
Arduino Integrated Development Environment (IDE)	Developing and uploading the control logic for the system.
Python	Developing the machine learning model for animal detection and behavior prediction.
YOLOv5	Building and training models for recognizing animal patterns.
Global System for Mobile Communication (GSM) communication libraries	Used to manage Short Message Service (SMS) sending and receiving functions.

Precision is defined as the ratio of true positives to the sum of true positives and false positives:

$$Precision = \frac{TP}{TP + FP}$$

Recall is defined as the ratio of true positives to the sum of true positives and false negatives:

$$Recall = \frac{TP}{TP + FN}$$

The F1-score represents the harmonic mean of precision and recall, combining both metrics into a single performance measure:

$$F1 - score = \frac{2 \times (precision \times Recall)}{(precision + recall)}$$

RESULTS AND DISCUSSION

The YOLOv5 algorithm demonstrated high accuracy and efficiency in identifying animals within both images and video streams. It recognizes animals quickly and precisely using cutting-edge object detection techniques, allowing for seamless integration into applications such as wildlife monitoring, livestock management, and animal research. The algorithm's ability to process images in real time improves the system's functionality and usability in numerous settings. Overall, these findings demonstrate the potential to transform animal detection and monitoring practices, making it a valuable tool for researchers, conservationists, and agricultural professionals alike.

When an animal enters the agricultural field, the camera detects its presence and sends the image to the processor. The processor analyzes the input and immediately sends an alert message, "Alert: Animal detected in the field," to the authorized person via GSM technology, without requiring an internet connection. The performance of the animal repellent system was evaluated using a confusion matrix, comprising true negative, true positive, false negative, and false positive values (Figure 4). The matrix contains few false positive and false negative recognitions.

Figure 4. Confusion matrix illustrating the performance of the YOLOv5-based animal repellent system.

The performance metrics for the model (Table 3) showed high effectiveness. The system achieved an accuracy of 97 %, demonstrating its capability to correctly identify instances of animals in the test dataset. The precision value of 95 % signifies that the system accurately identifies true positives with minimal false positives. Furthermore, a recall rate of 96 % reflects the system's proficiency in detecting a significant proportion of actual animal instances, indicating few false negatives. The F1-score, which balances precision and recall, is 94 %, underscoring the system's robust overall performance in accurately and consistently detecting animals. Collectively, these metrics confirm that the YOLOv5 algorithm is highly effective for the proposed animal repellent system.

Table 3. Performance evaluation of the proposed YOLOv5-based animal repellent system.

Performance metrics	YOLOv5
Accuracy	97 %
Precision	95 %
Recall	96 %
F1-Score	94 %

The performance evaluation of various classifiers for the proposed animal repellent system shows notable differences in accuracy (Table 4). The proposed method using the YOLOv5 algorithm outperformed all other classifiers, achieving an accuracy of 97 %, being the most effective of the tested classifiers at accurately detecting animals in the system. These comparative results provide strong evidence that the proposed approach is reliable, validating the model's robustness and effectiveness in real-world crop protection scenarios.

Table 4. Accuracy comparison of YOLOv5 and traditional classifiers in animal detection.

Classifier	Accuracy
Random Forest	89.6 %
Convolution Neural Networks (CNNs)	91.8 %
Support Vector Machine (SVM)	93.6 %
Recurrent Neural Network (RNN)	88.6 %
Proposed method (YOLOv5)	97.0 %

Despite its promising performance, the proposed system has certain limitations. First, detection accuracy may decrease under low-light conditions or adverse weather, such as heavy rain or fog, since the camera-based approach is sensitive to illumination. Second, although the dataset is diverse, it may not fully represent rare or region-specific species, potentially affecting generalization in real-world deployments. Third, the system relies on GSM modules to send alerts, which may be unreliable in areas with poor network coverage. Finally, while ultrasonic deterrents are generally effective, some animals may adapt to repeated exposure, reducing long-term efficiency.

While the proposed YOLOv5-based system demonstrates strong performance in real-time animal detection and deterrence, several avenues remain open for future research. First, the system could be expanded to cover larger agricultural areas by incorporating drone-based surveillance for broader monitoring. Second, augmenting the dataset with region-specific animal species would further improve detection accuracy and adaptability. Third, exploring advanced machine learning approaches, such as

YOLOv8 or hybrid deep learning models, could enhance precision under diverse weather and lighting conditions. Finally, integrating renewable energy sources, such as solar-powered modules, would promote sustainability and scalability of the system in rural farming communities.

CONCLUSION

In this work, we proposed an animal repellent system for crop protection using the YOLOv5 algorithm. The system demonstrated high accuracy, precision, recall, and F1-score, outperforming traditional classifiers. These results highlight the superiority of the YOLOv5 framework for real-time animal detection and deterrence in agricultural fields.

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