Design and Development of a YOLOv8-Based Automatic Repellent System for Preventing Crop Raiding by Peacocks

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Abstract. Peacocks have become a significant threat to agricultural fields, causing crop damage and affecting irrigation infrastructure. Traditional deterrence tools, such as scarecrows and nets, are often inefficient, labor-intensive, and environmentally unsustainable in the long term. To address this problem, this study proposes an automatic peacock deterrent system that combines deep learning-based detection with integrated actuation control. The system uses the YOLOv8 object detection model to detect peacocks in real-time video streams recorded using a web camera. When detected, a dynamically controlled Arduino-operated dual-servo pan–tilt mechanism is used to point a low-power laser at the target and start predator sounds to frighten birds. This approach provides a non-lethal, effective, and automatic visual–auditory deterrence mechanism. The system achieved a detection accuracy of 92.5% and a repellent success rate of approximately 90%, demonstrating effective and real-time performance of the proposed system. The proposed solution is effective in reducing manual intervention, improving crop protection, and supporting sustainable agricultural practices. This study highlights the capabilities of AI-based systems in precision agriculture and the alleviation of human–wildlife conflict.

1. Introduction

Birds play an essential ecological role in agriculture by assisting in pollination and regulating harmful insect populations. However, the same birds can also become a major problem when they start feeding on crops during the sowing, growing, or harvesting stages of the crop cycle. The Inter-Ministerial report of the committee on Doubling Farmers Income (DFI) – Volume X, titled "Risk Management in Agriculture," published by the Ministry of Agriculture, demonstrates how avian species cause losses in agriculture by harming crops during the sowing, seedling, and ripening stages, resulting in economic losses to the farming community.

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The report explains that bird damage varies depending on local population density, cropping patterns, season, and type of crops grown. A survey identified approximately 63 bird species that harm various crops, from cereals and pulses to fruits and oilseeds, while also indicating that some species are beneficial because they help control pests and rodents.

Fig. 1. Peacock presence in paddy field

Peacocks (Pavo cristatus), although culturally important, have become a significant source of crop raiding in most agricultural areas of India. They destroy vegetables, fruit crops, and irrigation equipment, such as drip pipelines and sprinklers, causing direct yield loss and damage to farm infrastructure. The increasing number of complaints involving peacocks in rural regions highlights the need for an automated, cost-effective, and sustainable deterrent. Conventional bird-scaring techniques include scarecrows, reflective tapes, wind-powered rotors, and unconventional deterrent techniques such as drumming and predator calls. Although these techniques are inexpensive, birds quickly habituate to repeated stimuli, rendering them ineffective after a short period. Other methods, including chemical repellents, fogging agents, and electric fences, have been partially unsuccessful and can raise environmental or other ethical issues.

The Humane Society of the United States (HSUS) provides non-lethal deterrents, such as low-current electric barriers and netting systems; however, these are usually time-consuming and expensive for large-scale practices. Laser-based bird repellents have proven to be a promising solution in recent years. Birds possess highly developed vision and are sensitive to moving laser light stimuli, which trigger avoidance behaviors. Laser-based systems are non-lethal and environmentally friendly because they operate silently compared to sound-based repellents; therefore, they are also environmentally friendly and highly effective against most bird species. It has been found that birds do not have the same ability to adapt to dynamic moving laser movements as they do with fixed sound devices; therefore, lasers are suitable for field use over a prolonged geographical area. However, most available laser deterrent systems are either manual or have a fixed pattern resolution and lack an intelligent sensing system. To overcome these constraints, artificial intelligence (AI) and computer vision can be used to facilitate the automatic detection and directed repelling of pest birds. Deep learning algorithms, including the You Only Look Once (YOLO) object detection system, have proven to possess remarkable real-time object detection precision for detecting animals and birds in mixed environments. This study proposes an automatic peacock repellent system that combines deep learning-based vision with a mechatronic actuation system. The system uses a YOLOv8 model trained using transfer learning to recognize peacocks in live videos captured by a webcam. When an Arduino Uno detects a bird, two servo motors are used to point a laser beam to the location of the detected bird and play predator sounds to help drive the bird away. The system was developed to operate autonomously with minimal human intervention and perform efficiently in real-time environments. Therefore, this would be an appropriate solution for minimizing crop losses due to peacocks.

1.1 Research overview

Bird deterrent systems have been widely researched to avoid crop damage caused by birds and to enhance agricultural productivity by automating and providing smart control systems. Permal et al. (2019) suggested an ultrasonic bird deterrent system that utilized beamforming on transmission lines based on hardware[1]. Conventional ultrasonic equipment will not operate because the sound wave travels in all directions, thus squandering energy in the absence of birds. Beamforming was implemented to direct ultrasonic waves toward bird-affected regions, thereby reducing energy loss. This design demonstrated that directional ultrasonic transmission could significantly enhance deterrence operations in critical infrastructures, such as transmission lines. Li et al. (2019) designed a bird repeller that uses audio transmission line towers and can easily adjust to the difference in species of birds [2]. They added acoustic sensors and adaptive control logic to their system to generate species-specific frequencies of audio to reduce the threat of habituation and maximize the repelling action. It was found that focused acoustic deterrence is capable of securing high-voltage equipment and can emerge as an environmentally safe method. Wang and Wong (2018) investigated the use of multiple bio-inspired unmanned aerial vehicles (UAVs) to conduct autonomous bird deterrence in vineyards.[3]. The UAVs were programmed to patrol specific areas with model predictive control (MPC) to react dynamically to any bird detected in the area.

Simulations conducted experimentally showed that two UAVs would be effective in the protection of a 40-hectare vineyard, which demonstrated that autonomous deterrent systems can reduce human intervention and operational costs. Cruz et al. (2020) proposed a new combination of an evapotranspiration (ET)-based irrigation controller and an automated bird deterrent system with a Raspberry Pi Model 3B +. The system calculated the ET rates by using the environmental parameters of solar radiation, humidity, wind velocity, and temperature using the Penman-Monteith equation to maximize irrigation. At the same time, the deterrent system implemented the image processing of the OpenCV library with the trained Haar cascade classifier to identify birds and provide a rotating red light as a deterrent mechanism[4]. The study demonstrated a high-saving of 15,931.72 mL of water as compared to the conventional systems and repelled Eurasian tree sparrows effectively, which showed the promise of integrated automation in agriculture. Srividya et al. (2021) adopted a bird deterrent system, based on deep learning, to automatically detect and scare birds with the help of convolutional neural networks (CNNs). The machine identified the presence of birds in a certain area and compared the received images with the pre-trained collections to verify the presence of birds. When it was detected a high-decibel sound was emitted to scare birds off. This model was very accurate demonstrating the effectiveness of CNNs in real-time, autonomous deterrence in farmlands [5].

Sharma et al. (2021) compared real-time object detection models, which included Tiny-YOLO, YOLOv2, YOLOv3, and Mask R-CNN to detect birds, especially the Indian house sparrow. Their findings showed that Tiny-YOLO was appropriate in systems that could be only run on a limited number of computational powers, but that YOLOv3 achieved the best detection accuracy, which proved the consistency of deep learning in identifying birds in a dynamic agricultural setting [6]. Brown and Brown (2021) designed and tested robotic laser scarecrows to manage the bird damage in sweet corn. The system employed a portable robotic unit that had a green laser to display moving beams around fields. In a three-year field experiment, plots treated with lasers recorded significant destruction of bird's relative to the non-treated controls and this demonstrates that laser-based deterrents are a viable, non-lethal substitute to crop protection [7]. So et al. (2020) went a step further to incorporate a PTZ (Pan-Tilt-Zoom) camera and intelligent laser system on the Caffe framework of real-time bird recognition and targeting. Their mechanism was an automatic tracking of birds through vision detection and direct laser beam to the bird at the time of perching on the target zone which led to instant flight action. This paper has highlighted the benefits of integrating computer vision with laser technology so that there would be efficient, selective, and automated deterrence [8]. The researchers of Hidayatulloh et al. (2022) designed a laser bird deterrent device with a diverticulum based on Arduino and tailored to rice fields. The system utilized laser sensors to detect movement and servo motors to move it and was controlled by Arduino Uno microcontroller. It has been successful in substituting manual methods of scaring birds with an automatic process of identifying and scaring birds that came close to the crops. It was a low cost, simple to use design, and offered dependable operation in small sized agricultural applications [9]. All these studies point to a high tendency of automation and integration in bird deterrent. Ultrasonic beamforming, UAV patrolling, AI-based image recognition, and laser targeting are techniques that have ensured increased accuracy and dependability of deterrence. Nevertheless, the majority of the literature is concerned only with detection and repulsion, and the fact that they can be integrated with other systems of smart farming or sources of renewable energy is frequently left out.

The article by Cruz et al. (2020) is unique in that it embodies a combination of irrigation management and deterrence based on Raspberry Pi, which demonstrates that multifunctional automation in agriculture is possible [4]. The ideas can be extended to future developments by using renewable energy, including running it on solar power, and adjusting it to the needs of particular species, such as peacocks, to achieve the sustainability, scalability, and environmental friendliness. A solar powered audible bird-scarer experimented on different species of birds and specifically on crows, which are the most harmful species of birds in the Indian farmland. The researchers compared the use of 22 predator sounds eagle, owl and falcon and found that the predator sounds that worked best were those of the falcon. It also discovered that volume, frequency, and rate of repetition of the sound were also dependent factors to success [10]. The system was stable and able to be used in the long run in outdoor. On the same note integration of wind and solar-powered bird Repeller which targets on small and marginal farmers. The wind-powered one utilized mirror reflectors and plastic blades to generate sunlight reflections that disturbed birds and the solar-powered part also used motors and metal plates based on a control circuit powered by NodeMCU. The introduction of IoT also enabled wireless timing and switching control that increased efficiency and convenience to the user [11]. Deployment of smart protection mechanism, where the Wireless Sensor Network (WSN) and an IoT based surveillance system was proposed to detect peacocks that destroy crops in Tamil Nadu. Sensor nodes and communication modules were also utilized by the system to track the movement of the birds and automatically issue deterrents. This approach was aimed at non-toxic control of wild animals and preservation of crops [12]. Lastly, a system that was AI-driven was used to scare birds and flocks on the fruit orchards that were about to be ripe. The system implemented the convolutional neural networks (CNNs) which had been trained to detect bird flocks in the video shots in real-time. The module activated the actuators when flocks were seen, which minimized unnecessary use of power and habituation. The precision, recall, and F1-score of the algorithm in detecting movements of birds among other objects was verified and demonstrated the user that the algorithm is highly accurate [13].

2. Methodology

The proposed system can automatically identify the presence of peacocks in agricultural fields and trigger repellent measures. It is a combination of a deep learning-based image recognition system and a basic mechatronic system with a microcontroller. The entire workflow comprised four steps: image acquisition, YOLOv8 detection, signal processing, and activation of the repellent.

2.1 System overview

The system operates on the principle of continuous field monitoring using a web camera placed at a high altitude. A live video stream was introduced to a computer containing a trained YOLOv8 model, which successfully identified peacocks at various angles and distances. The model transmits a signal to the Arduino Uno via a serial interface when peacocks are detected. The Arduino then uses two servo motors to point a laser module at the detected position and simultaneously triggers predator sounds through a speaker connected to it.

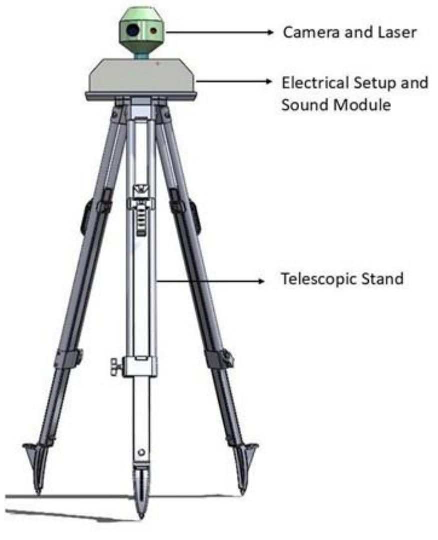

Fig. 2. CAD Model of Automatic Repellent System

The CAD model of the system, shown in Figure 2, illustrates the mechanical arrangement and housing used for *integrating* the laser, camera, and servo mechanisms. The design provides accurate positioning of the laser and camera axes to enable *precise* targeting. The servo mount provides two rotational degrees of freedom (pan and tilt) for dynamic tracking, and the upper housing shields the components from dust and outdoor conditions.

2.2 Hardware Components

2.2.1 Microcontroller unit

An Arduino Uno was used as the central control unit. It receives serial data from a host computer that executes the YOLOv8 detection model and converts these signals into motion and activation signals for the servos, laser, and sound modules of the robot to be activated. Adequate communication was facilitated using the standard Firmata firmware, which supports Python scripts and Arduino via a USB serial interface.

2.2.2 Servo Motors

Two SG90 micro servo motors were used to enable the laser pointer to move in two directions. The servos were mechanized at right angles to provide horizontal (pan) and vertical (tilt) rotations so that the laser beam could be precisely aimed at the location of the detected peacock. The coordinate data sent to the YOLOv8 system were used to dynamically update the servo angles to ensure continuous tracking of the moving bird.

2.2.3 Laser Module

A 5 mW, 650 nm red laser module was used as the primary visual deterrent. The laser was mounted on top of the camera and operated using one of the Arduino digital output pins. Under the detection of a peacock, the laser allows an automatic switch to a bright visible line, which scares the bird and chases it.

2.2.4 Sound Module

The audio-based deterrence was attached to an external speaker, which was connected to the Arduino. Predator calls (saved as MP3 files) were broadcast via a speaker using the pygame library in the Python environment. The sound system is synchronized with the laser, and it creates visual and auditory stimuli, which will be effective in scaring the peacocks off without harming them.

2.2.5 Camera Unit

The vision sensor of the system is a USB webcam. It streams the live video frames of the agricultural field and transfers them to the YOLOv8-based detection software running on a computer. The captured images were processed in real time to determine the presence of peacocks, and the detection result was immediately transmitted to the Arduino for actuation.

2.2.6 Power Supply

Each module operates on a 5 V regulated DC power supply, which can be energized by a solar-battery hybrid unit for deployment in isolated areas within the agricultural areas. To avoid voltage drops and maintain operational stability, the servos and laser were not connected to the logic circuit of the Arduino.

2.2.7 *Telescopic stand*

The mechanical section consists of a base frame in the form of a telescopic stand to adjust the movements and hold the electrical components.

2.3 Software Implementation

The software framework integrates deep-learning-based object detection with the real-time control of repulsive devices. A custom dataset comprising 1,200 peacock images was prepared using real-time field video recordings and controlled agricultural observations. High-definition video streams were converted into individual frames that were curated to ensure diversity in lighting conditions, background environments, bird orientations, and partial occlusions, which increased the representativeness of the dataset for downstream visual recognition tasks. The resulting images were automatically labeled using the Roboflow platform with the support of the Ultralytics YOLO annotation pipeline to guarantee the creation of accurate bounding boxes in the selection of the YOLO format. This computerized process ensures reproducibility and reduces human annotation bias. The images were resized to the same size of 640 × 640 pixels, which is a compromise that is compatible with the YOLOv8 training framework and provides the optimal trade-off between computational needs and real-time inference. A uniform resolution is essential to ensure that the feature extraction layers in the network are supplied with spatially homogeneous inputs. A dataset with a 80:10:10 split was used to divide the dataset into training, validation, and testing subsets. Horizontal flipping, brightness variation, and scaling were data-augmentation schemes used to improve model generalization in the dynamic field setting. YOLOv8s (a smaller version) was selected because it provides a reasonable combination of computational performance and detection rates.

The training was performed based on the Ultralytics framework, which enables the achievement of optimized performance under edge-compatible, real-time deployment conditions. The training validation showed consistent convergence and high detection confidence scores. Therefore, the model achieved is highly suitable for real-life agricultural applications, with a scalable capability for the real-time detection of peacock populations across varied environmental settings. Python was used on the host computer and Arduino Firmata on the microcontroller to implement the system. The peacocks in the live video feeds were detected precisely using a custom-trained YOLOv8s.pt model. The model was loaded with Ultralytics and processed frames acquired through the web camera. The algorithm selects items that it finds based on a confidence threshold of 0.55 and the recognized class of peacocks. To enhance accuracy, more filtering is performed by color analysis: the identified area is converted into HSV and YCrCb color spaces to calculate the ratio of blue and skin pixels. This was done to ensure that the system distinguished peacocks from humans and background objects with similar characteristics. When the location of a peacock was detected, the centroid coordinates of the bounding box were transformed into servo angles through the numpy.interp() function of mapping pixel position to 0–180° servo position.

The calculated angles are sent to the Arduino through serial communication in the form of <servoX>, <servoY>, <flag>\n where flag is 1 to make the repulsive system active and 0 to switch it off. A multithreaded architecture was used to ensure smooth video processing. YOLO detection was performed in a separate thread, and there was minimal latency between acquiring a frame and responding to it. Simultaneously, the Pygame audio library was used to play sounds of the predator in non-blocking mode, which enabled continued detection and actuation without frame drops. In response to the detection of a peacock, the laser and sound were turned on, and the servos were synchronized with the dynamics to follow the position of the peacock. When the bird flies out of the frame, the sound is switched off, and the servos are repositioned at their neutral (90°, 90°) to avoid unnecessary firing. This integrated design effectively combines computer vision, real-time signal processing, and microcontroller-based actuation to form a closed-loop system for autonomous peacock deterrence in agricultural fields.

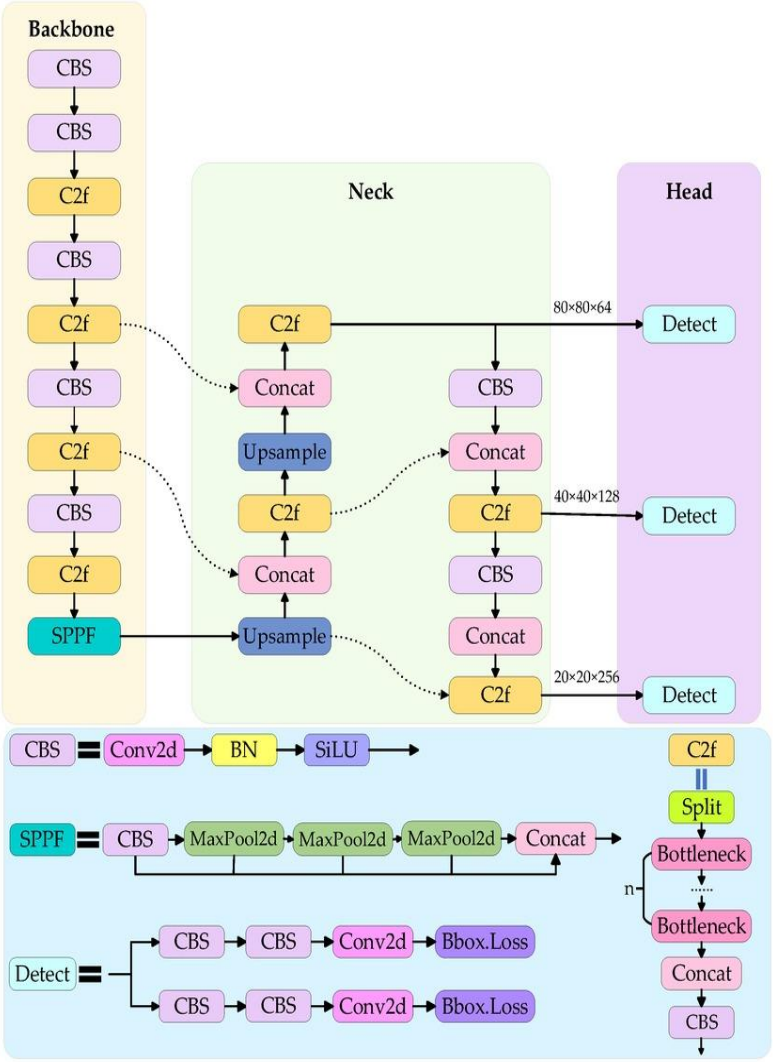

Fig. 3. Architecture of YOLOv8 showing the backbone, neck, and detection head[14]

2.4 Working Principle

Live video frames are processed on the computer with the use of the YOLOv8s.pt model. The model marks the coordinates of the bounding box when it recognizes a peacock in any frame. These coordinates are then computed to give servo positions based on the direction of the bird in the camera view. These positional instructions are passed on to the Arduino which then commands the servos to move to direct the laser beam to the target that was identified. Meanwhile, a sound of a predator is introduced to support the effect of repulsion. When the bird moves out of range or not detected, the system turns off the laser and sound.

2.5 Flow chart

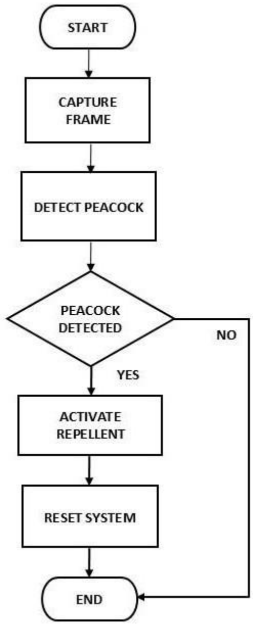

Fig. 4. System flow chart

3. Result and Discussion

3.1 System Testing Setup

The prototype of the automatic peacock repellent system was tested under real agricultural conditions. The setup included a 5-meter observation range using a USB webcam mounted on a tripod at 1.2 meters height, facing the field edge. The Arduino Uno, laser module, and dual servo arrangement were powered by a 5V supply, while the Python-based detection and control software ran on a laptop equipped with an Intel i5 processor and 8GB RAM. For testing, a dataset consisting of real-time peacock videos and live field observations was used to validate the YOLOv8 detection model. The trained model achieved an average confidence level exceeding 90% for clear sightings and 82% for partially occluded views, demonstrating strong robustness under real-world conditions. To further evaluate performance, a comparative analysis was conducted with earlier YOLO variants, including YOLOv5 and YOLOv7. While YOLOv5 achieved an average detection accuracy of 91.3% and YOLOv7 reached 93.8% mAP50, YOLOv8 outperformed both models with a maximum mAP50 of 95.2% and improved localization stability. Additionally, YOLOv8 demonstrated reduced detection latency and better handling of small-scale or partially occluded objects, making it more suitable for real-time agricultural deployment. The average time of detection-to-action was about 0.65 s, and this is appropriate in a real-time deterrence system. False activations were greatly reduced by the color ratio filtering in more complex field scenarios involving movement of leaves, shadows, or human action. False detection was less than 6%, demonstrating the efficiency of the two-stage filtering system to differentiate between peacocks and background movement and human interference. The consistency of the model predictions and the actual field conditions is verified by the detection output and it allows confirming that the system is capable of autonomous deterrence.

Fig. 5. Prototype of bird-deterrent system

3.2 Detection and Control Response Performance

The YOLOv8 model successfully detected peacocks with high accuracy in a 5-8 m vision range. Each detection produced one bounding box of the bird that enabled the laser to be directed by the servo-controlled laser to the center of the area being detected. Based on the training and validation loss curves in Figure 6 (Box Loss, Class Loss, and Object Loss), the model has rapidly converged and stabilized its learning at approximately 80 epochs, which demonstrates that the model was able to reduce localization and classification errors. The robustness of the detection is also supported by the performance statistics in Figure 7 (mAP50, mAP50-95, Precision, and Recall) which gives a maximum mAP50 of 95.2% and a recall of 93.4%.

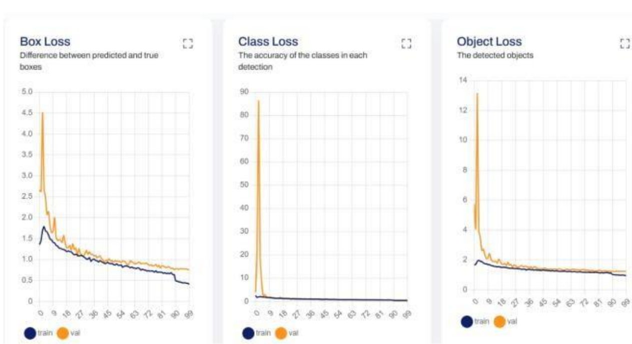

Fig. 6. Training and validation loss curves of the YOLOv8 model

3.3 Repellent Effectiveness

The deterrent reaction was measured on basis of the response of birds following laser and sound activation. In the field testing, immediate avoidance behavior was demonstrated initially by peacocks in the 4-5 m range, that is, they fled or ran away at the origin of the source of the sound and light. The average time (10 seconds) that the 90- percent of the detected birds left the observation area after activation of the system was 10 seconds. Laser-based visual deterrence coupled with predator sound playback proved to be more effective than either of the two methods used separately. The proposed system was also dynamic that it was able to target the location of the bird unlike the conventional scarecrow or inactive deterrents that stayed still thus habituating. The birds did not exhibit habituation, across repeated trials, and they avoided the tendency to respond with the same behavior during the observation period.

3.4 System Stability and Operational Limitations

The prototype was very stable with continuous operation of several hours. The servo positioning was also accurate and had very little jitter or lag following rapid moving objects. But the performance was a bit lower in low-light or foggy scenarios, when the visibility of the camera was minimal, and the YOLOv8 detection accuracy was lower than 70%. The laser light was also less visible on the daytime sky and therefore reduced its range of deterrence. The processing load was another limitation which was realized as the YOLO model used CPU, which when peak movement was reached, the speed of detection might reduce to less than 10 frames per second. This will be solved by implementing the model on a GPU or edge Artificial Intelligence board (such as NVIDIA Jetson Nano) to get real-time performance in the later versions.

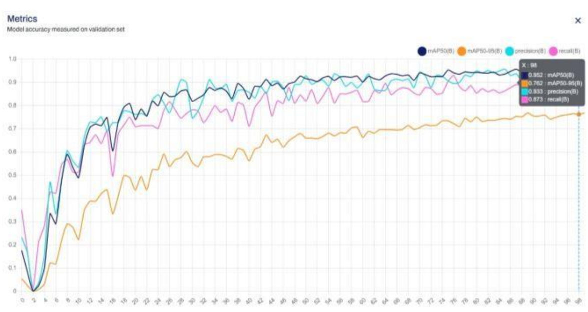

Fig. 7. Performance metrics of the YOLOv8 model

3.5 Comparative Discussion

The proposed system is non-contact, automated, and adaptive compared to the traditional deterrent, i.e., scarecrow, bird nets, and reflective tapes. In contrast to mechanical or non-moving devices, the given system is based on machine sight and AI, which means that it will only recognize target species such as peacocks without affecting helpful birds and animals. Additionally, its low- power nature and photovoltaic friendliness make it the best to be used in low-electricity rural agriculture fields. The comparison between traditional and proposed systems can be summarized and presented in Table 1 and will show that the efficiency of detection, energy efficiency, and deterrence will be improved.

Table 1. Summary of results

PARAMETER	OBSERVED VALUE	REMARKS
Detection Confidence(Clear View)	92.5%	Accurate Identification
Detection Confidence(Partial View)	~82%	Moderate Reliability
False Detection Rate	<6%	Effective Reliability
Detection to response time	~0.65 s	Real Time Operation
Repellent Success Rate	90%	Birds Moved Away
Continuous Operation	5+ HOURS	Stable and Safe
Power Requirement	5V, 2A	Easily Solar Supplied

3.6 Discussion Summary

The findings prove the hypothesis that the combination of the YOLOv8-based vision with dual-axis servo laser control and predator sound emission provides a cost-effective and sustainable approach to crop protection. The fact that the system is self-monitoring to detect, intercept, and repel peacocks proves that it can be used to cut down agricultural losses and will not require a lot of manual intervention. Enhancements in the future might involve thermal vision in night vision, optimization of AI models and multi-sensor fusion in separating species of birds.

3.7 Ethical considerations

The system was designed to repel peacocks without causing physical harm. A low-power Class II laser (<5 mW) was used, ensuring eye safety and compliance with Class II laser safety standards. The predator sound levels were maintained below harmful acoustic thresholds. The system only triggers temporary deterrence responses and does not injure or trap the birds. All field testing was conducted with care to avoid ecological disturbance [6]

4. Conclusion and Future work

This study has been able to demonstrate how an automatic peacock repellent system can be developed, which involves computer vision and control embedded in a system to protect farms. The system uses a deep learning model YOLOv8 to identify peacocks in real-time with live video feeds. After identifying a target, a low-power laser is also pointed at the bird dynamically by the Arduino-controlled dual-servo mechanism and a predator sound is also turned on to add to the deterrence. Experimental findings made it clear that there is an accuracy of 92.5% and a general repellent percentage of 90% confirming that the combination of the visual and auditory deterrent method is effective and safe. It was also shown that the system operated in a stable mode, enabled fast response (around 0.65 seconds), and had low false detections, since the system had intelligent colour filtering. The system will help mitigate one of the main factors that break the crops in the rural areas because of the detection and repulsion process, which is automated to enhance the stability of farmers' incomes and sustainable farming. Moreover, the solution avoids harmful chemicals and nets, making it an environmentally sustainable and ethical alternative to the traditional methods of controlling birds.

4.1 Future work

Despite the positive performance of the prototype, it can be expanded in a number of areas to be scaled and made robust in the real-world application:

- Night-Time Operation: By including infrared or thermal imaging sensors, the sensor will be reliable in detecting in low-light-level or during the night. The YOLO model can be deployed on edge devices (NVIDIA Jetson Nano or Raspberry Pi 5) to minimize latency as well as allow the model to operate in the field in a fully autonomous mode without relying on a laptop.
- Multi-Species Detection: It is possible to broaden the application of the system by adding other species that attack crops (e.g., parrots, crows, or monkeys).
- IoT and Remote Monitoring: It may be adapted with wireless connectivity (LoRa or GSM) that will allow farmers to view detections, system status, and deterrence events in real-time via a mobile dashboard.
- In general, the suggested system offers a reliable platform on which subsequent AI management of wildlife and precision agriculture tools can be implemented. It can become a scalable and intelligent deterrent platform that protects crops sustainably by having a better sense, quicker inference, and intelligent energy systems.

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