Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 10s (2025)

Detection of Birds Intrusion and Their Expulsion Using Iot and Deep Learning Techniques

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Article History:

Received: 02-01-2025

Revised: 25-02-2025

Accepted: 20-03-2025

Abstract:

Millet crops such as pearl millet, Sorghum, foxtail and Fruit crops, such as watermelon, cucumber, grapes and Cereals like wheat, rice, and maize are particularly vulnerable to bird damage in the weeks leading up to harvest. Crop damage caused by birds is one of the major threats to reducing crop yield. Traditional methods followed by farmers are not effective in protecting crops from birds. Since the safety of both humans and birds is equally vital, it is important to protect the crops from damage caused by birds as well as divert them without any harm. Thus, in order to overcome the above problems, the smart IoT and deep learning based birds detection and expulsion system was developed. For this, four GoPro cameras were placed at each of the quadrant corners of a 30-by-30-meter agriculture field to provide continuous monitoring. Videos were captured at thirty frames per second in 1080p resolution. Fuzzy Contrasting-Limited Adapting Histogram Equalization (FCLAHE) is a preprocessing filter used to improve image contrast and detection accuracy under different lighting situations. The proposed system uses Mask R-CNN for instance segmentation, which enables accurate bird localization and segmentation. The main detection model is the YOLOv8 algorithm, which is optimized for real-time performance. In order to boost farming precision, this study offers a real-time bird intrusion and expulsion detection system that makes use of deep learning and the Internet of Things. Experimental tests show a 98% detection accuracy, outperforming current techniques in terms of accuracy and efficiency for real-time applications. The scalable, self-sufficient, and economical solution for managing bird intrusions provided by this research greatly reduces the need for manual intervention and minimizes losses, thereby advancing IoT-driven smart farming.

Keywords: Bird Intrusion and Expulsion Detection, Deep Learning, IoT-Based Smart Farming, Mask R-CNN Segmentation, YOLOv8 Object Detection

1. Introduction

The growing importance of the Internet of Things (IoT) in people's lives has resulted in a notable increase in the number of breaches against various IoT devices. Because IoT devices are usually installed in environments with limited resources and processing power, and because it is challenging to gather malicious traffic samples, traditional deep learning algorithms are ill-equipped to detect intrusions in IoT networks [1]. To prevent bird damage, numerous studies have been carried out in urban and industrial settings as well as on farms, orchards, seafood farms, and airports [2]. Due to the exponential growth in network threats, detecting intrusions has been a well-studied topic for many decades. Due to the advancement of web-based communication systems in recent years, the necessity for network security has increased [3]. Deep learning (DL) is becoming increasingly popular in all academic fields because of its dominance in training massive amounts of data [4]. The necessity for strong safety mechanisms to identify and disclose such threats is growing increasingly pressing as Network of Things (IoT) networks expand quickly [5]. The identification challenge is an example of a fine-grained classification task, as it is difficult to identify between different bird species due to the minute habits that are hidden to the human eye [6]. Presented a convolutional neural network (CNN) with case segmentation that uses photos taken by an unmanned aerial vehicle (UAV) to identify transmission towers and bird nests [7]. The three networks that make up YOLOv4 are the head, neck, and backbone networks. CSPDarknet-53 serves as its backbone network. Darknet-53 is 53 layers of convolution deep and uses Stochastic Pyramids Pooling (SPP) for extracting features [8]. R-CNN without R, you look only once (YOLO), mask R-CNN, one blast detector, deconvolution solo shot detector, region-based convolutional networks, and fast R-CNN were tested for their detection performance. YOLO has the best speed performance, according to the comparison results, whereas mask R-CNN has the strongest detection capabilities [9]. Finding effective and lightweight computer vision techniques is crucial because IoT devices are restricted in memory and CPU capabilities. For example, obtaining a history of moving things and classifying them using Fourier definitions (FD) and classifiers, as well as YOLO (You Only Look Once) to distinguish between birds and rodents [10].

This is the main contribution of the proposed method:

- Excellent quality (1080p, 30 FPS) video analysis and constant tracking are guaranteed by GoPro-based real-time monitoring.
- Using FCLAHE as a preprocessing filter improves image contrast, visibility, and detection precision under various lighting scenarios.
- Mask R-CNN was used for precise bird localization and segmentation.
- YOLOv8 algorithm, which is tuned for IoT devices, has been developed for fast, real-time bird detection.
- Outperformed traditional models in terms of accuracy, efficiency, and scalability, achieving 98% detection accuracy.

The remaining sections will be organized as follows: Section 2 covers the relevant information, which is the literature review for our proposed plan; Section 3 describes the suggested approach; Section 4 explains the experiment and data analysis; and Section 5 describes the study's conclusions and future directions.

2. Objectives

To develop a real-time, non-invasive bird detection and expulsion system for agricultural fields using Internet of Things (IoT) technologies and deep learning models, also accurately identify and segment birds in agricultural fields with high precision using YOLOv8 and Mask R-CNN and to minimize crop losses and manual intervention through automated, non-invasive bird deterrence.

3. Related works

Nahida Sultana et al. [11] have proposed a convolutional Neural Network (CNN) technique, we are able to identify the image. Deep Learning has made significant strides in computer vision and has evolved over time. Tingyao Jiang et al. [12] have suggested, a order to increase efficiency and capture greater contextual information, YOLOv7's backbone uses a novel dynamical convolutional kernel called ODconv, which is specifically made for recognizing small and packed targets.

Asia Mahdi Naser Alzubaidi et al. [13] have recommended, a bird detection in photos using an efficient and successful animal detection system. The Single Shot Multibox Identification (SSD) model proposed in this work, MobileNet SSD, can handle objects with varying shapes and viewing angles. Yong Zhanget al. [14] have described, a lightweight YOLOv8-AMD rice leaf infection detection model may suffer from image distortion and loss of delicate features during the recognition process since the area of diseased rice leaves is quite tiny in real-world rice growth settings.

Shan Suthaharan et al. [15] have suggested, a cardinal and sparrow photos from a new backyard birds dataset that was taken from RGB movies and used to build an ANN model using a frequency-driven training technique. Xi Chen and Zhenyu Zhang et al. [16] have reported, a combining information distillation with neural architecture search, the Bird-YOLO method accurately identifies birds. Prior to training, image pretreatment and dimension grouping of previous boxes are done to reduce noise interference.

Li Yunlong et al. [17] have proposed a deformable DETR (DEtection TRansformer)-based bird and UAV detection technology to help airports better monitor the clearance area and lower safety risks. Shahan Azeem et al. [18] have reported, an assays for diagnosing and tracking the Avian Influenza Virus in poultry.

Miodrag Bolic et al. [19] have proposed a combination of doppler and camera fusion, the joint classification network uses the camera network to extract deep, complex elements from the vision and the radar network to extract spatiotemporal elements from the radar track. Wilmar Hernandez et al. [20] have recommended, a using methods of transfer learning to a new domain with insufficient photos to train the entire model in order to gain an excellent property extractor from the first domain.

Eduardo Aquiles Gutierrez-Zamora et al. [21] have proposed, a automated technique to identify, locate, categorize, and track hummingbirds in high-speed video, precisely estimating the frequency of their wingbeats through signal analysis and computer vision techniques.

4. Methods

First, input data is gathered, including photos of birds in horticultural fields, and then FCLAHE preprocessing is applied to improve image quality and eliminate noise, guaranteeing precise detection. After preprocessing, segmentation is done using Mask R-CNN, which offers comprehensive instance segmentation to identify individual birds. Then, the YOLOv8 algorithm is used to detect, identify, and locate birds in the scene in real time. Lastly, to reduce the possibility of crop damage, the system recognizes bird intrusions and initiates an automated expulsion mechanism.

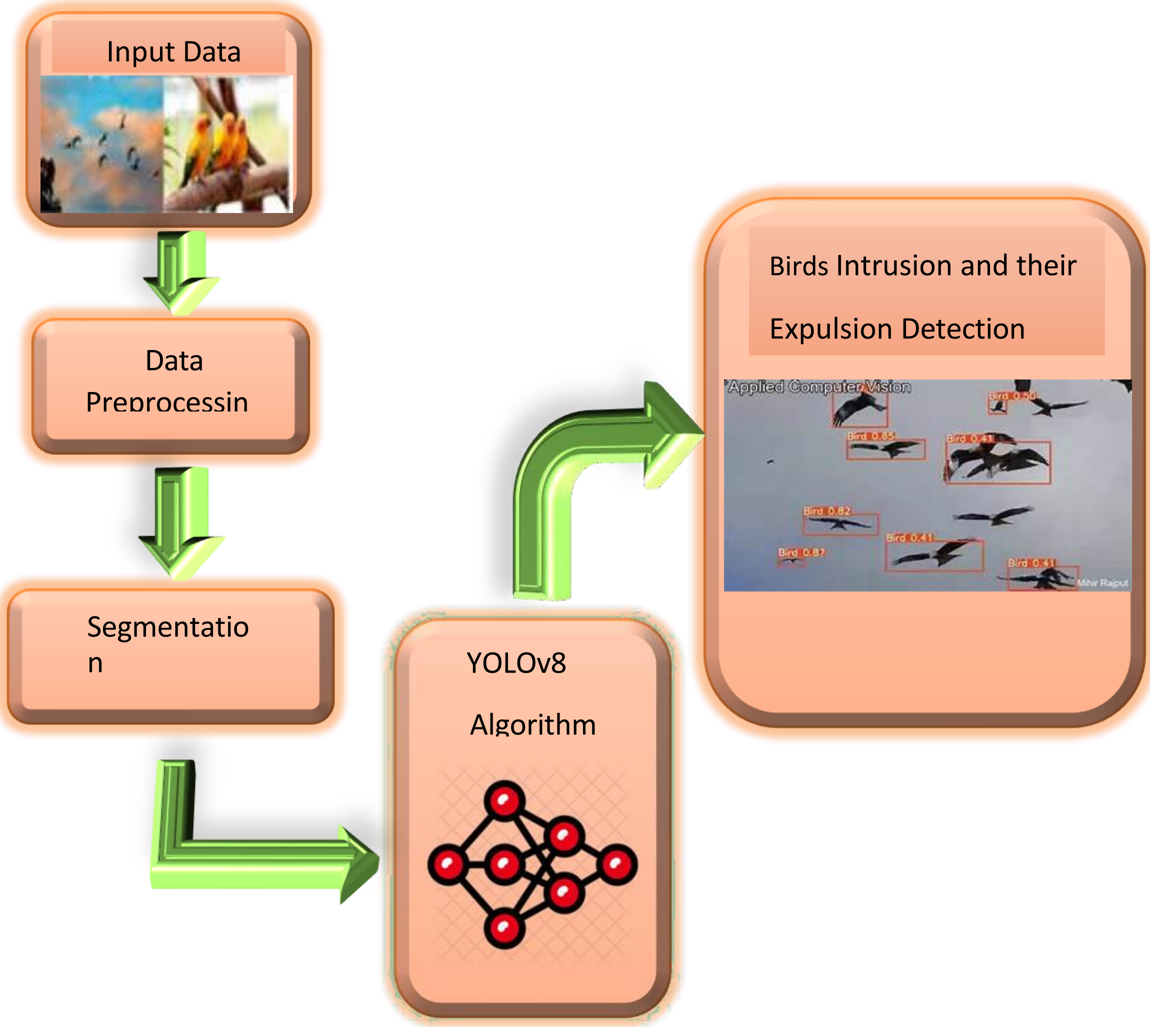

Figure1: Proposed approach work flow

The workflow of the suggested methodology for bird intrusion and expulsion detection, which consists of data collection, preprocessing, segmentation, and algorithm selection, is shown in Figure 1.

4.1 Data Preprocessing

Our preprocessoring filter, fuzzy contrast-limited adaptive histogram equalization (FCLAHE), is developed in this section. A fuzzy function in a new form that uses the image's gray level statistics to give a non-linear correction. The fuzzy function, which is defined as follows, assigns a membership value between 0 and 1 to the pixels according to the difference between their gray levels and a seed point, which is situated at the mass core:

$$p = 1 / (1 + \beta d) \quad (1)$$

where d represents the difference in intensity between p and a seed point, β regulates the function's opening, and p is the intensity of the pixel being evaluated. Here is a description of the fuzzy contrast-limited adaptive histogram equalization (FCLAHE) non-linear filter that we suggested:

$$\hat{J}(x,y) = A_r(x,y) + (J(x,y) - A_r(x,y))F(|J(x,y) - A_r(x,y)|) \quad (2)$$

A pixel's initial intensity at coordinates (x, y) is represented by (x, y). The same pixel's new intensity in the processed image is represented by $\hat{J}(x, y)$. With the exception of background inhomogeneities, (2) assumes that the pixel intensities at a radial distance (r) from the seed point are comparable. When a bright area of the backdrop (caused by background inhomogeneities) is present, $J(x, y)$ will diverge more from Ar; that is, $J(x, \ ) – Arx, y = \Delta J_r (x, y)$ will yield a greater value. Because of this, $(\Delta Jr\ x, y)$ will produce a smaller value, as per (1). This will cause the second term on the right side of (2) to weaken, and $\hat{J}(x, y)$are to be given A_r. (0) will produce unity, which in return assigns $\hat{J}(x, y)$to $J(x, y)$, if there are no inhomogenieties in the surrounding environment. This means that A_r. will be near $J(x, y)$, i.e. $\Delta J_r (x, y) \approx 0$. Indeed, homogeneities or small areas with a strong contrast in the surrounding environment are eliminated by equation (2), which could be confused for actual lesions in the segmentation procedure that follows. The suggested equation also preserves the mass core's contrast and brightness.

4.2 Mask R-CNN Segmentation

In order to assess the model and make sure it fits data that hasn't been seen yet, Mask R-CNN uses a multi-loss function during learning. The function of loss is calculated as a weighted sum of all the losses that occurred during training at each stage of the architecture on each proposal ROI, and it is defined as follows:

$$L = L_{Class} + L_{Bbox} + L_{Mask} \quad (3)$$

L_{Class}, or the loss of segmentation, illustrates how the predictions converge to the actual class. RPN and Mask R-CNN heads are trained using L_{Class}, which combines the segmentation loss. The decrease in the size of bounding box, or L_{Bbox}, measures how successfully the model locates objects. It integrates the $Bbox$ adaptation loss with the RBN and R-CNN mask heads during training. Here's how L_{Class} and L_{Bbox} damages are calculated:

$$L_{clas}(p, u) = -log p_u \quad (4)$$

$$L_{Bbox}(t^u, V) = \sum i \in \{z, y, w, h\} [L_1^{smooth}(t_i^u - v_i)],$$
$$\text{where } L_1^{smooth}(z) = \begin{cases} 0.5\, x^2 & if\ |z| < 1 \\ |z| - 0.5 & otherwise \end{cases} \quad (5)$$

For any positive $Bbox$, the word pu denotes the expected probability of the basis class u. stand for the class u and the basis $Bbox$ predicted Bboxes, respectively. In $Bbox$ vector offset, the term i stands for core value (z, y), width, and height. For each class of the Kclasses, the mask head creates k binary masks of length $m \times m$, giving it a dimensional output of $Km2$. As the average cross-entropy of binary pairs for the assumed masks correlated with the ground truth, $LMask$ (the loss of dividing up the predicted mask) is calculated as follows:

$$L_{Mask} = -\frac{1}{m^2}\sum 1 \leq i,j \leq m\left[h_{ij}\, logp_{ij}^{k} + \left(1 - h_{ij}\right)\log\left(1 - p_{ij}^{k}\right)\right] \quad (6)$$

With a pixel (i, j) in the center of the truth mask for a ROI of size $m \times m$ having a class label whose probability is h_i, and a pixel in the mask created for class k having a prediction label of p_{ij}.

4.3 Yolov8 Algorithm

With a primary focus on real-time bird detection in a field, YOLOv8 is an efficient object detection system.

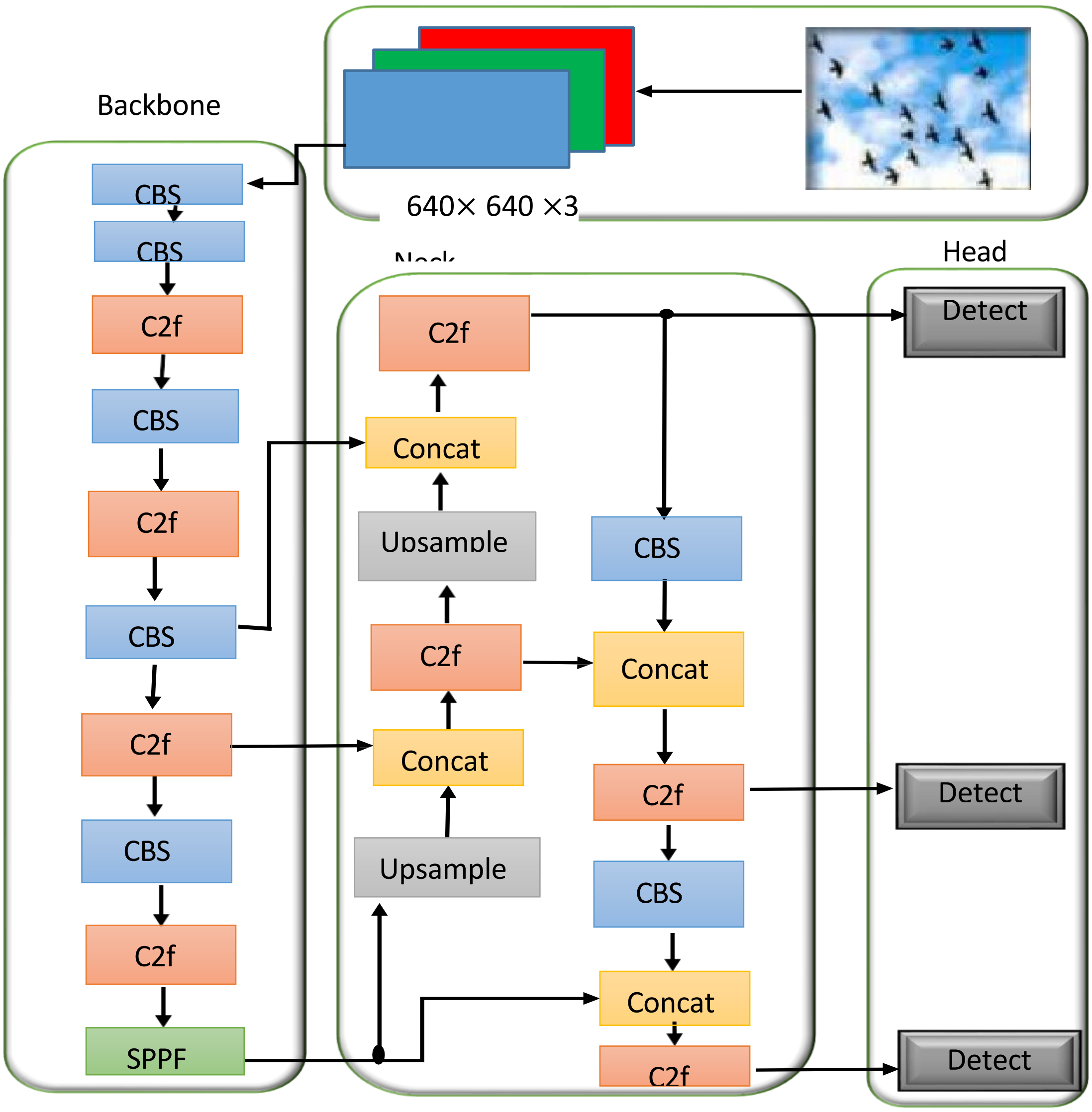

Figure2: Framework for detection of the proposed algorithm

The model's operation involves first dividing a picture into a grid and then predicting the box's borders and likelihoods of classes in each grid cell. This indicates that it has the ability to locate multiple things in an image at once. The accuracy of YOLOv8 is likewise noteworthy, but it's also quick. Data annotations and multi-scale training are two of the methods that are employed (to provide handling of diverse object sizes). It suppresses overlapping or superfluous bounding boxes using non-maximum suppression (NMS).

This qualifies YOLOv8 for applications such as horticulture bird detection, where prompt and precise detection is necessary to support systems. In order to estimate the class possibilities and confidence ratings for each grid, YOLOv8 breaks every picture into grids after processing every single image of the birds. The suggested YOLOv8 algorithm's detection framework is displayed in Figure 2. YOLOv8 is made up of the Head, Neck, and Backbone. Backbone: YOLOv8m's backbone is something called CSP Darknet53. The purpose of it is to extract features from the pictures.

Neck: The model's neck makes use of Feature Pyramid Networks (FPN) and Path Aggregation Networks (PAN). All of the backbone's feature maps are combined in the neck. Head: Anchors are not used by the head of YOLOv8m, unlike previous YOLO versions. Rather, it makes a direct prediction about the location and nature of the objects, which speeds up and simplifies the procedure. The primary function of the head is to make predictions.

4.4 Performance Evaluation criteria

The suggested YOLOv8 Algorithm's performance is evaluated using four commonly used classification metrics: accuracy, recall, precision, and F1-score. The usefulness of the suggested Iot model is thoroughly evaluated by these metrics, with accuracy being a crucial component in determining the model's overall precision. Using equation (7), this evaluation metric may be calculated:

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (7)$$

The accuracy is determined by dividing the total number anticipated positive cases by the number of accurately anticipated positive cases. Equation (8) is used to calculate this evaluation metric, as indicated below:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (8)$$

It is possible to evaluate the testing accuracy of the proposed YOLOv8 method using the F1-score, which is the inverse mean of precision and sensitivity (recall). Equation (9), which is displayed below, can be used to calculate this assessment metric:

$$\text{F} - \text{score}(\%) = 2 \times \frac{recall \times presicion}{recall + presicion} \quad (9)$$

Recall measures the model's ability to find all pertinent positive cases. Recall can be computed by:

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (10)$$

5. Results

5.1 Dataset

The field experiment was conducted at our native agricultural land. A 30 m x 30 m land was selected for bird activity monitoring in the agricultural land, Since the birds were small and usually far away from the cameras, 1080p videos were captured. The four corners of the pitch were equipped with four GoPro Hero 4 cameras. To account for variable levels of birds activity, four video segments were harvested from a single camera viewing angle, and one video segment was gathered from a different camera viewing angle (Table 1). Manual verification was done on over 100 distinct arriving and leaving bird actions. To evaluate the algorithm's performance, over 8,712 frames were manually reviewed. In order to evaluate the algorithm already available birds images and datasets were added to the newly created dataset**.**

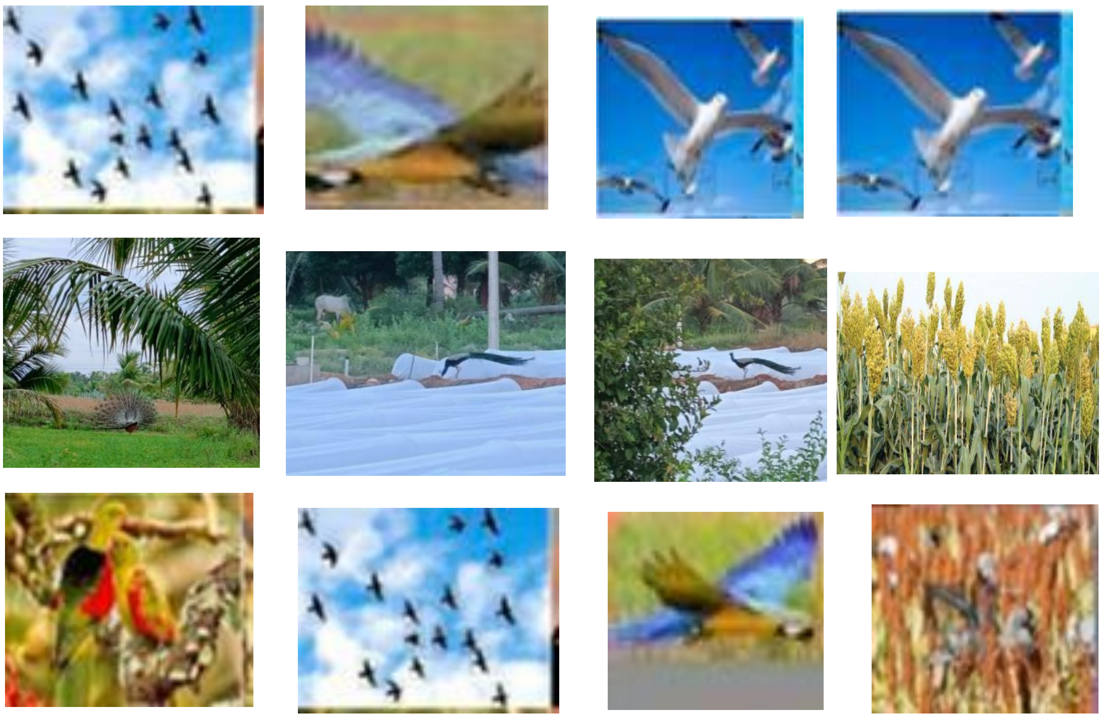

Figure 3: Several bird species' input data during the stages of intrusion and expulsion

The dataset includes a variety of bird species, backgrounds, and flight patterns, which improves model generalization. Some of the birds often feed on millets and other fruit crops, and depending on their size and position in relation to the camera, flying birds appeared to have up to a few hundred pixels in each image frame (Figure 3).

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 10s (2025)

Table 1: Data for detecting intrusions and expulsions

Camera no	View of the Camera	Density of bird populations	No of frames	System Intrusion bird count	System Expulsion bird count
1	2	High	901	32	17
2	2	Medium	1501	13	4
3	3	Low	3603	6	10
4	2	High	905	32	18
5	2	Medium	1802	11	2

These datasets aid in the development of systems to detect and expel birds from horticulture fields, reducing crop damage.

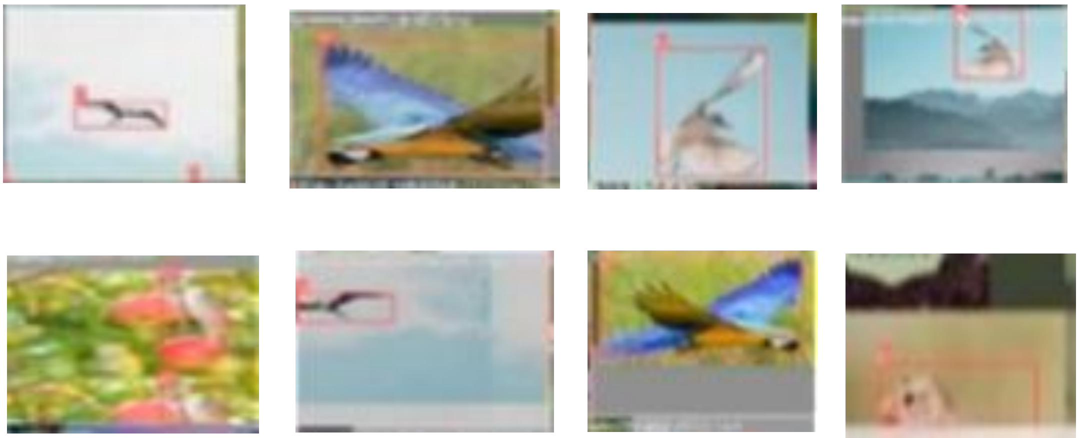

Figure 4: The YOLOv8 algorithm is used to detect bird intrusion and expulsion

Figure 4 displays the train results, which include the images obtained after the YOLOv8 model was trained as well as the outcomes following the video prediction. Because of its great precision and speed, the YOLOv8 model effectively identifies birds in vineyards or farmlands, preventing crop damage.

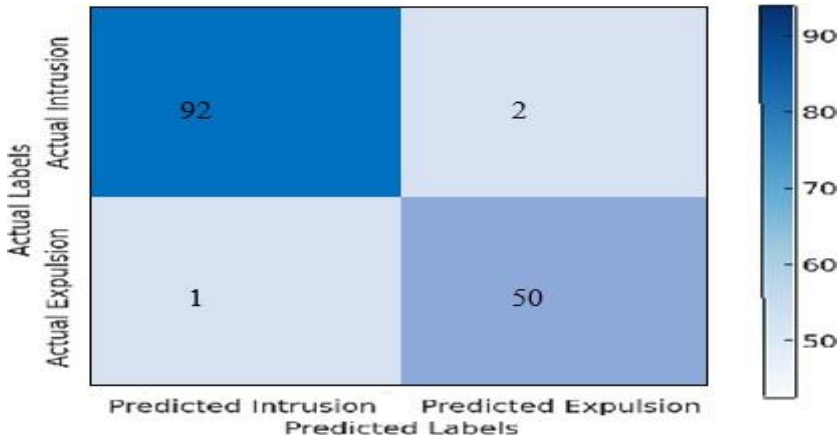

Figure 5: Confusion matrix for bird intrusion and expulsion detection using YOLOv8

This real-time detection guarantees that birds can be ejected before they cause damage. The performance of a bird intrusion and expulsion detection system is visually represented by the confusion matrix in Figure 5, which assesses the system's classification accuracy between the two categories of intrusion and expulsion. Each of the matrix's four quadrants represents the proportion of events that were successfully or wrongly classified. when real bird invasions were accurately identified as such. This high number shows that bird invasions are successfully detected by the system. Expulsions were incorrectly classed as actual incursions. These mistakes imply that certain bird invasions were not accurately identified, either as a result of model limitations or contextual influences. The classification of actual expulsions as invasions was incorrect. This mistake suggests that the system occasionally mixes up ongoing incursions with expulsion occurrences. Expulsions were accurately identified as such. The ability of the system to precisely identify and validate successful bird expulsions is indicated by a higher TN value.

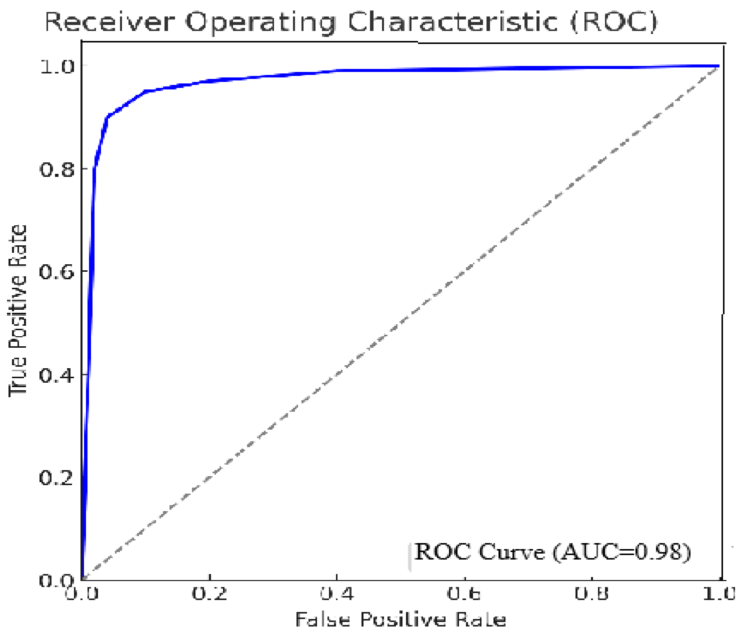

Figure 6: YOLOv8 bird intrusion and expulsion detection model's ROC curve

Figure 6 displays the ROC curve for YOLOv8 bird incursion and expulsion detection model. The performance of the bird intrusion and ejection detection system is evaluated using three main metrics: Precision, Recall, and F1-Score. With a precision of 97.87%, the model was accurate in 97.87% of the cases it identified as bird invasions. A model that successfully reduces false positives and ensures fewer inaccurate intrusion detections is indicated by a high precision rating. With a recall of 98.92%, the model was able to accurately identify 98.92% of real bird invasions. A lower recall indicates that some intrusions were overlooked, resulting in false negatives. This metric assesses how well the system records actual intrusion occurrences. A balanced trade-off between precision and recall is reflected in the F1-score of 98.40%, which is the harmonic mean of the two. The model retains good detection performance while lowering mistakes, as seen by a better F1-score.

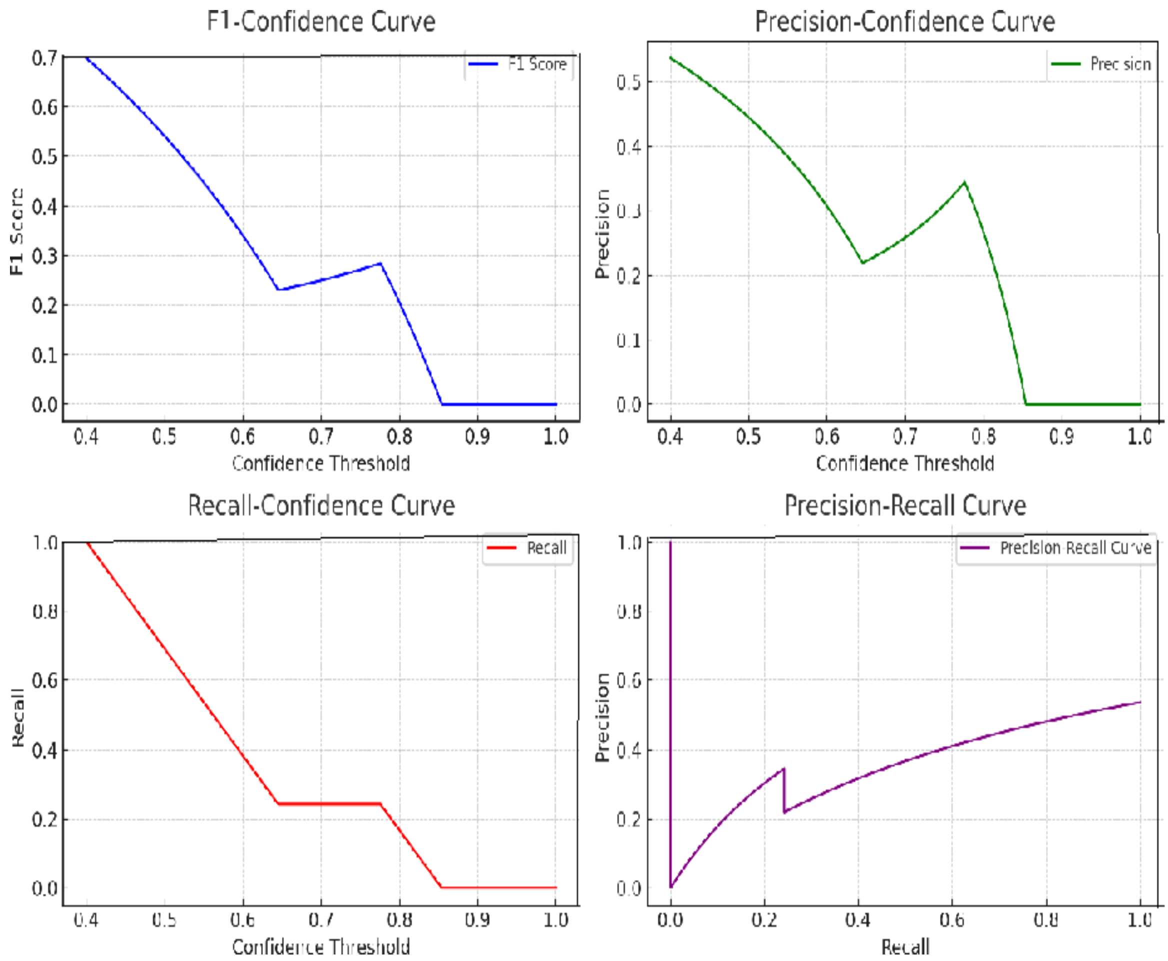

Figure 7: The F1-confidence curve, precision-confidence curve, recall-confidence curve, and precision-recall curve are among the graphical results that are displayed following the YOLOv8 model.

The performance evaluation of the bird incursion and expulsion detection system utilizing F1-score, precision, recall, and their relationship with confidence levels is depicted in the set of graphs in Figure 7. These curves help to maximize decision-making in classification tasks by offering information about the model's performance at various confidence levels.

The bar diagram in Figure 8 displays the entering and outgoing bird activities for each of the movies used in this experiment, demonstrating the effectiveness of the bird counting technique. Performance of the bird detecting approach was examined in terms of true detection, false observation and missing detection. Most of the videos were from camera 2 FOV. Camera 2 was situated adjacent to tall trees that served as bird shelter. Videos from this camera view were categorized as having a high or medium bird population density because there were more birds observed on this side than on any other side. The intended approach also produced a higher number of incoming and exiting birds for the video taken from this field of view (Table 1). This is because Camera 3's field of view was comparatively open, which limited the speed at which birds could move between the trees and treetops.

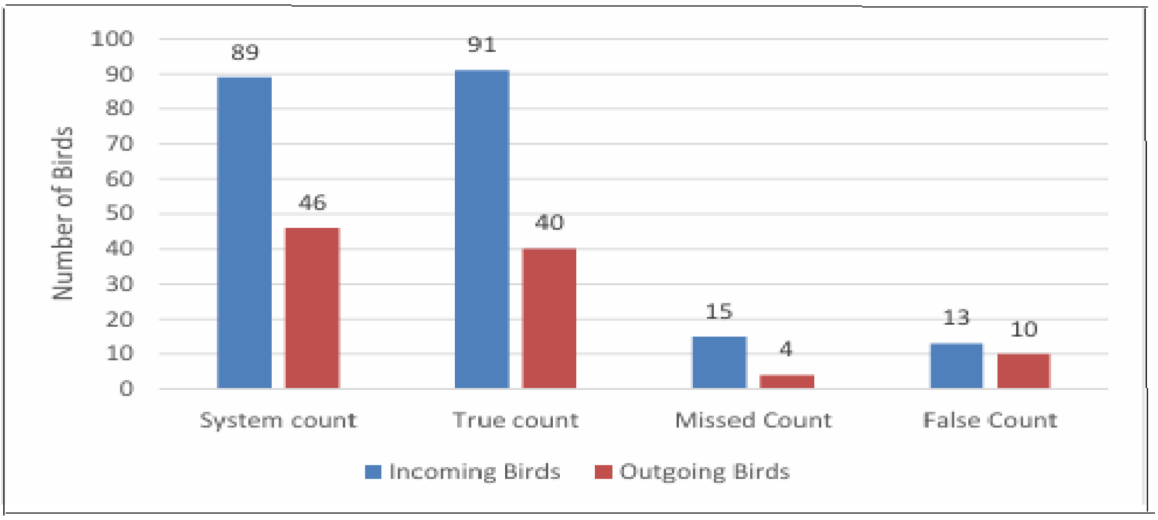

Figure 8: A bar graph showing the estimated number of birds using the suggested approach

A bird's size and position changed quickly between frames when it was flying close to the camera. In these situations, the tracking class will start the same bird as the new detection even though it has been detected several times. Based on the performance criteria shown in Table 2, the suggested algorithm exceeds all current approaches in terms of accuracy, efficiency, and real-time feasibility, making it the superior alternative for automated bird infiltration and expulsion detection.

Table2: Performance indicators for different approaches

Topics of Detection	Using algorithm	Accuracy ratio
Identification of the supplied picture (bird) trained using samples [22].	YOLO	81%
Detection of the object without close PASCAL VOC Test supervision 2019 [23].	DSOD300	77.7%
CNN detection of the input image (bird) [24].	YOLOv3	95.52%
Proposed Method	YOLOv8	98%

6. Discussion

In order to safeguard horticulture areas, this study proposes an intelligent and effective framework for detecting bird entrance and expulsion that makes use of deep learning and the Internet of Things. The suggested technique guarantees high accuracy (98%) while using a camera by combining YOLOv8 for real-time detection with Mask R-CNN for accurate bird segmentation. The model is a scalable, autonomous, and economical solution for smart farming, as demonstrated by experimental evaluations that show it outperforms current methods in both detection efficiency and real-time application. The system's scalability, efficiency, and flexibility for wider agricultural uses will be the main goals of future improvements. First, incorporating multi-sensory information such as motion and audio signals—can improve bird detection, particularly when sight is poor. Second, expulsion effectiveness can be increased by enhancing the automated repeller mechanism with AI-driven adaptive deterrent tactics, including changing sound frequencies or using drones. These advancements will enhance the system's reliability and effectiveness in precision agriculture.

Acknowledgement

This project was funded by the All INDIA COUNCIL FOR TECHNICAL EDUCATION (AICTE), India, AQIS ID: 1-932769/831, to conduct of Project under Research Promotion Scheme (RPS).

References

[1] Li, Zeyu, and Wenbin Yao. "A two stage lightweight approach for intrusion detection in Internet of Things." Expert Systems with Applications 257 (2024): 124965.

[2] Pyon, S. U. B. O. N. G., J. O. N. G. S. U. So, Junhyok Pak, Jinzu So, Sunil Kim, and DPROF KOREA. "Development and Efficacy of Laser Bird Repeller with PTZ Camera and Caffe Framework." EARTH SCIENCES AND HUMAN CONSTRUCTIONS 4 (2024): 17-24.

[3] Roy, Dharani Kanta, and Hemanta Kumar Kalita. "Enhanced Deep Auto encoder-Based Reinforcement Learning Model with Improved Flamingo Search Policy Selection for Attack Classification." Journal of Cybersecurity and Privacy 5, no. 1 (2025): 3.

[4] Kocher, Geeta, and Gulshan Kumar. "Machine learning and deep learning methods for intrusion detection systems: recent developments and challenges." Soft Computing 25, no. 15 (2021): 9731-9763.

[5] Fraihat, Salam, Sharif Makhadmeh, Mohammed Awad, Mohammed Azmi Al-Betar, and Anessa Al-Redhaei. "Intrusion detection system for large-scale IoT NetFlow networks using machine learning with modified Arithmetic Optimization Algorithm." Internet of Things 22 (2023): 100819.

[6] Pillai, Sofia K., M. M. Raghuwanshi, and Prerna Borkar. " Super resolution Mask RCNN based transfer deep learning approach for identification of bird species, International Journal of Advanced Research in Engineering and Technology 11, no. 11 (2021): 2020.

[7] Satheeswari, D., Leninisha Shanmugam, NM Jothi Swaroopan, and Nirmala Venkatachalam. "Mask R-CNN based Object Detection in Overhead Transmission Line from UAV Images." In International Conference on Image Processing and Capsule Networks, pp. 639-653. Cham: Springer International Publishing, 2022.

[8] Huang, Zhanchao, Jianlin Wang, Xuesong Fu, Tao Yu, Yongqi Guo, and Rutong Wang. "DC-SPP-YOLO: Dense connection and spatial pyramid pooling based YOLO for object detection." Information Sciences 522 (2020): 241-258.

[9] Bharati, Puja, and Ankita Pramanik. "Deep learning techniques—R-CNN to mask R- CNN: a survey." Computational Intelligence in Pattern Recognition: Proceedings of CIPR 2019 (2020): 657-668.

[10] Shim, Kyuwon, Andre Barczak, Napoleon Reyes, and Nasim Ahmed. "Small mammals and bird detection using IoT devices." In 2021 36th International Conference on Image and Vision Computing New Zealand (IVCNZ), pp. 1-6. IEEE, 2021.

[11] Mashuk, Farhan, Abdus Sattar, and Nahida Sultana. "Machine learning approach for bird detection." In 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), pp. 818-822. IEEE, 2021.

[12] Jiang, Tingyao, Jian Zhao, and Min Wang. "Bird detection on power transmission lines based on improved YOLOv7." Applied Sciences 13, no. 21 (2023): 11940.

[13] Alsaadi, Elham Mohammed Thabit A., and Asia Mahdi Naser Alzubaidi. "Automated bird detection using SSD-mobile net in images." In AIP Conference Proceedings, vol. 3097, no. 1. AIP Publishing, 2024.

[14] Fu, Yingan, and Yong Zhang. "Lightweight Rice Leaf Disease Detection Method Based on Improved YOLOv8." Engineering Letters 33, no. 2 (2025).

[15] Suthaharan, Shan. "A frequency-driven deep learning technique for bird segmentation and detection from RGB video." In Applications of Machine Learning 2023, vol. 12675, pp. 287-292. SPIE, 2023.

[16] Chen, Xi, and Zhenyu Zhang. "Optimization research of bird detection algorithm based on YOLO in deep learning environment." International Journal of Image and Graphics (2024): 2550059.

[17] Shanliang, Liu, Li Yunlong, Qu Jingyi, and Wu Renbiao. "Airport UAV and birds detection based on deformable DETR." In Journal of Physics: Conference Series, vol. 2253, no. 1, p. 012024. IOP Publishing, 2022.

[18] Azeem, Shahan, and Kyoung-Jin Yoon. "Diagnostic Assays for Avian Influenza Virus Surveillance and Monitoring in Poultry." Viruses 17, no. 2 (2025): 228.

[19] Mehta, Varun, Fardad Dadboud, Miodrag Bolic, and Iraj Mantegh. "A deep learning approach for drone detection and classification using radar and camera sensor fusion." In 2023 IEEE Sensors Applications Symposium (SAS), pp. 01-06. IEEE, 2023.

[20] Rosero-Montalvo, Paul D., Pınar Tözün, and Wilmar Hernandez. "Optimized CNN architectures benchmarking in hardware-constrained edge devices in IoT environments." IEEE Internet of Things Journal (2024).

[21] Bastidas-Rodriguez, Maria Ximena, Ana Melisa Fernandes, María José Espejo Uribe, Diana Abaunza, Juan Sebastián Roncancio, Eduardo Aquiles Gutierrez Zamora, Cristian Flórez Pai et al. "Estimating Wingbeat Frequency of Hummingbirds using a No-labeling Learning Computer Vision Approach." Integrative And Comparative Biology (2025): icaf001.

[22] Sitepu, Ade Clinton, Chuan-Ming Liu, Mula Sigiro, Joel Panjaitan, and Venkatesh Copa. "A convolutional neural network bird's classification using north American bird images." International journal of health sciences 6, no. S2 (2022): 15067-15080.

[23] Shen, Zhiqiang, Zhuang Liu, Jianguo Li, Yu-Gang Jiang, Yurong Chen, and Xiangyang Xue. "Object detection from scratch with deep supervision." IEEE transactions on pattern analysis and machine intelligence 42, no. 2 (2019): 398-412.

[24] Asna, Sumaya Islam, Md Rakib, and Abdus Sattar. "Image Based Bangladeshi Bird Detection and Classification through Deep Learning." In 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), pp. 1-7. IEEE, 2024.