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AUTOMATED CROP SECURITY: A DEEP LEARNING APPROACH TO DETECTING AND DETERRING BIRDS INTEGRATED WITH A LASER SYSTEM

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Most people depend on agriculture for their livelihood. Farmers' income is closely linked to crop yield, which has been decreasing due to natural factors and a lack of advanced technology. Birds play a vital role in the ecosystem, but they can also significantly affect crop yield. The birds often damage grain crops, so special attention is needed to address the harm they cause. Controlling the birds is important in farming to prevent the loss of food. In the article, we developed an automatic system to deter birds. The system uses deep learning to detect birds and deter them from crop fields. When a bird enters the farm, the system identifies its location through a picture taken by a camera, and the trained model gives instructions to the laser controller to deter the bird from the crops. This model is trained on the dataset (Bird-feeder). The results show that the trained model performed well, achieving a validation accuracy value of 96.02%, macro F-1 scores of 96.5 %, macro precision of 95.8% and macro recall of 95.4%. The trained model can detect even small birds with accuracy. Farmers can use this model to improve the production of their crops by deterring the birds.
Key Points: Deep Learning; YOLOv11; Automatic Birds Detection and Deterrence; Real Time Object Detection; Agriculture.

Introduction

Agriculture plays a vital role in the economies of underdeveloped or developing countries. Agriculture is a leading sector in the economic growth of Pakistan [1]. It is one of the most important activities of humans. From the beginning, this has been

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the only source of food for the people. Even today, agriculture is a vital part of modern life. Agriculture provides us with food, Clothes for wearing, wood for furniture, and materials to build homes. Agriculture is not just about growing animals; it is linked to health, economy, and the development of society. Agriculture is the backbone of Pakistan economically and contributes significantly to the nation's roundabout 19% of national GDP [2]. It provides jobs to Millions of people. Farmers, agricultural workers, Drivers, and sellers depend on agriculture for their income. Economic increases occur as agricultural production increases. It improves the standards of people living in the villages because it is the main source of income in the villages. Agriculture also provides raw materials to the industries, for example, cotton is used in the textile industry, sugarcane in the sugar industry to produce sugar and ethanol, wheat is used in flour mills, and seeds are used to produce Oils, soaps, and other products. It plays a huge role in international trade. Many countries export and import agricultural products and earn money to grow their country's economy. Agriculture can support the environment. Trees help to clean the air, provide us with many types of fruits, and reduce CO_2.

Fruits contain vitamins and minerals, which are very important for our health.

However, agriculture in Pakistan is facing several challenges [3], one of which is the interaction between birds and agricultural activities. Birds have a dual role in agriculture. While they offer significant benefits like pest control, pollination, and seed dispersal, they can also be a source of harm, especially when they damage grains, fruits, and vegetables[4].

Birds play a serious environmental performance in the health and regularity of several bio-networks [5]. Birds that often attack farms are a big problem in farming areas near forests. These attacks damage crops and lead to large financial losses for farmers [6]. Managing bird populations through a combination of deterrents and habitat management is key to minimizing their negative effects while maximizing the benefits they provide to crops [7].

Related Work:

Traditional bird control methods are harmful to the lives of birds and the environment [8]. There have been only a few studies focused on protecting crops from potential damage caused by things like weather [9], floods,

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and other threats by the use of images. The most common birds in Pakistan are Maina, Peacock Crow, Sparrow, Parrots, Aves, etc. These birds are the main contributor that harms the crops in Pakistan.

These studies, which use basic image processing techniques [10], have two main issues. First, the process of extracting important features often requires users to do it manually instead of being done automatically. The second problem is that these methods are not very reliable or adaptable to new data, making them less useful for different situations. Because of this, smarter methods are needed. Specifically, there is a gap in using computer-based methods to identify and classify rapeseed damage without causing any harm. Many methods are used to deter the birds, such as lidar, radar thermal images. They used background subtraction to increase the accuracy of the detection system [11]. These methods were not providing good results. Modern agriculture uses technology, for example Automatic irrigation system. Weather monitoring, drones, and sensors. Artificial intelligence (AI) and Machine learning are being used to detect diseases and predict yields.

In recent years, different deep learning techniques such as RNN, Mask RNN [12], Faster-RNN [13], and Yolo [14] have been used to detect birds. This study aims to fill that gap with a new and powerful method called deep learning, which doesn't require direct involvement from humans.

Deep learning is used in many areas because it works well. Deep learning models use neural networks, and the neural networks have greatly improved tasks like sorting images [15]. Deep learning models are good at finding complex patterns in data, especially when the data is unstructured, like images, text, or sensor data. These models automatically learn to identify more complex features as you move through different layers of the network, and they use these features for classification [16], [17]. The best part is that this entire process happens automatically, without any direct input from humans, which is a major advantage of the deep learning model [15].

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Figure 1-birds attacking crops

Figure 2-Traditional Harmful Methods to deter birds

Figure 3-Common birds found in Pakistan

In this article, we have designed an automatic system that automatically detects the birds and deters them by using the deep learning approach Yolo (Yolov11). This System does not injure the birds, and it is harmless for birds and humans [18]. The freedom from relying on past knowledge and human involvement in feature design is a major advantage of the YOLOv11 model [15]. The system includes three parts: The Detection unit, the Computing unit, and the laser control unit. Firstly, the camera takes a picture. The picture is checked in the Deep Model sent by the detection unit. If the birds are found, they are deterred by a laser emitted by the Laser Control Unit. This system is made to prevent birds from

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becoming familiar with the laser, making it work better.

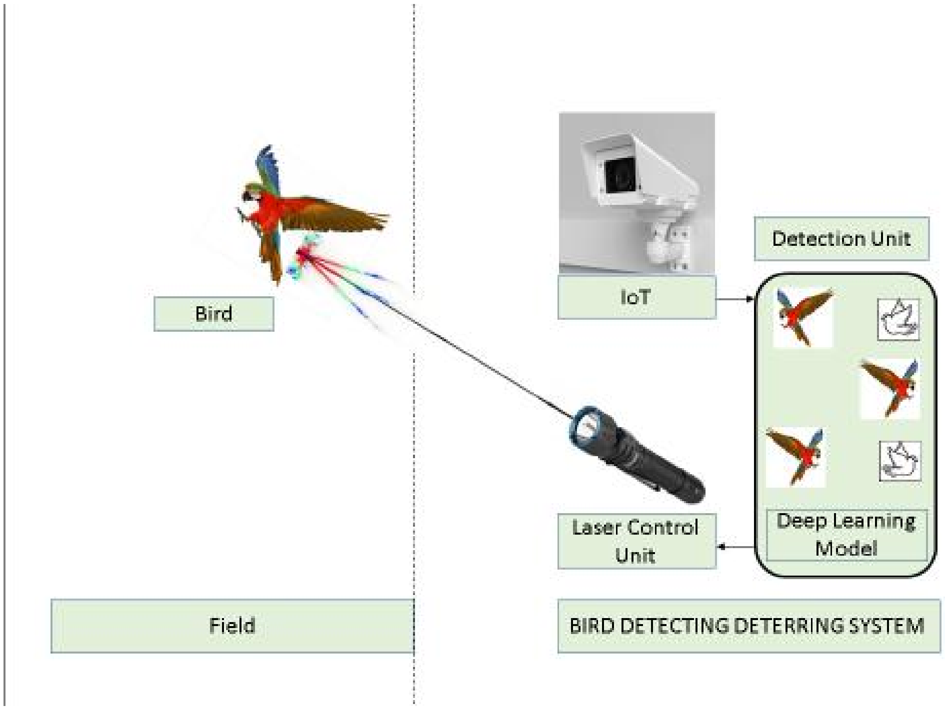

Figure 4-Bird Detecting Deterring System (BDDS)

TOOLS AND APPROACHES

Choosing Models and Capturing & Annotating Image Data for Better Results

In this study, we built a system to detect birds using pictures captured by a camera. A deep learning approach called YOLOv11 is used in the detection model. Yolo (you only look once) is a one-step stage detector[14] introduced in 2015. It is very efficient, simple, and fast as compared to other models [12][19][20].YOLO has twice times more average precision [14]. Yolo is used in real-time applications [21]. Many object detection methods work well for finding objects, but they struggle with detecting birds because birds are often very small in the image [22]. Also, background noise and objects that block the birds make it even harder to detect them. So, we used the Yolov11 model to improve bird detection in outdoor environments, even if they are very small in size. However, the success of this model depends on having good-quality images for training. To create a reliable bird

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detection model, two main tasks were completed. First, we had to gather many pictures of common birds to teach the model. Use a good-quality camera with motion detection at a farm or crop field. The camera took pictures at a resolution of 1920×1080 pixels whenever a bird moved within its view. Second, the pictures needed to be annotated for deep learning. We used the VGG Image Annotator software to label the birds in the images [23]. The next step is to create a dataset to train and test the model. The dataset has three sections. The training section has 88% bird images, the validation section has 08% images, and the test section has 04% targeted images.

Analysis of Bird Detection Model

After training and checking the desired model, we check the "optimized common bird detection model." How it works using the test dataset. Keep in mind two important things: the lowest detection confidence (LdC) and the limit for intersection over union (IoU). As the desired model detects a targeted bird, it allocates a confidence score between 0 and 1. A higher value means the model is more certain that it has correctly identified what it's looking for. Once we set a minimum detection confidence, the model will only consider targets with a confidence score above this threshold. If the intersection over union (which measures how well the predicted target matches the actual target) exceeds a certain threshold, the detected target is considered valid.

If the value of Intersection over Union is higher than the set threshold, the target is given a true positive (TP); else, a false positive (FP). If the model fails to detect the common bird in the image, then it gives a false negative (FN) value. After the predictions, two pointers, Precision and Recall**,** are used to measure the performance of the desired model. Higher values of indicators show the model is working well and properly. When the model is integrated into the laser system, the system generates one laser at a time to deter them away individually. Precision is more important than recall. A high value of precision means the system can more effectively and accurately target and repel birds[22]. The formulas for measuring the precision and recall are given below.

$$Percision = \frac{TP}{TP+FP} \text{ -----1}$$

$Recall = \frac{TP}{TP+FN}$-----2

The low confidence level is between 0.90 and 0.95, and the IoU threshold (between 0.5 and 0.1. The IoU threshold of 0.1 is used to focus on detecting the area around the birds; by doing this, we can reach the goal of the model. Analyzed the setting that gave the best results and divided the dataset into two groups based on the size of birds (larger or smaller) to see how bird size affects detection.

Automatic Bird Detecting and Deterring System. The automatic detecting and deterring system consists of three main parts:

1. **DETECTION UNIT** consists of a camera that takes pictures as input and sends the pictures to the computing unit, in which the trained model is installed.

COMPUTING UNIT uses an embedded system (Jetson TX2) to run the model. The system will run on Ubuntu 18.04, and Python is used to execute the model and communicate with the system parts. As the input is received by the trained model, it checks whether the image contains a bird picture are not. If the trained detects the picture of a bird in the image, it instructs the laser control unit to take action to deter the bird by pointing to the location of the bird.

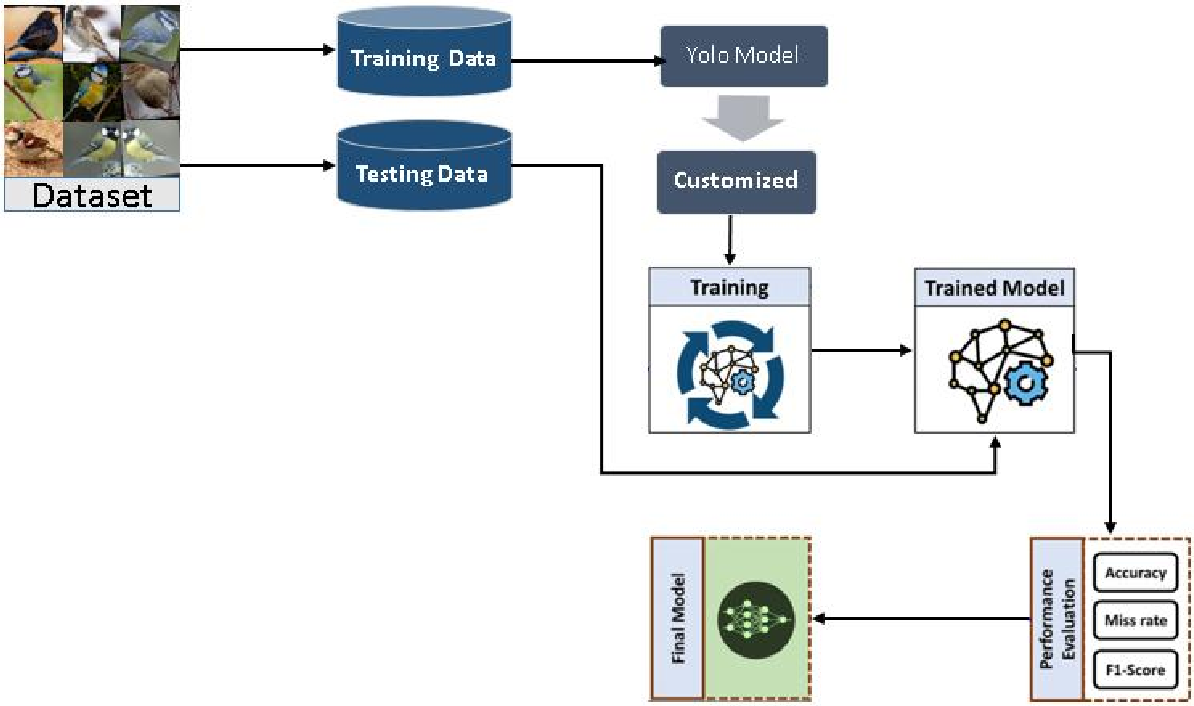

Figure 5-Trained Model

LASER CONTROL UNIT consists of a relay and a motor control chip. The relay controls a 400-mW green laser, which can be turned on and off by signals from the embedded system. The chip is coupled with two other motors that control the laser's direction. Since the system is designed for outdoor use, it needs to be protected from the weather and kept cool according to the environment. The system is connected to a 110-V AC power supply, and the laser unit is powered by a switch. In the laser rotation mechanism, the first motor rotates the laser horizontally, and the second motor controls the vertical rotation. During the operation period, the system allows the camera to take a picture. Then the model checks the image to detect any birds in the picture. If no bird is found, the system simply checks the time again. If birds are found, the system activates the laser by controlling the relay and also moves the motors to aim the laser at the birds to deter them. After this, the motors come back to their original positions. The

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system checks the time again; if the duration of time is outside the operation period, the system waits (10 minutes) before continuing.

Laser Data Capture Plans

The system works by first detecting the birds. The efficiency of the system depends on two key factors: the detection model and the laser method of scanning. A better detection model improves the bird-deterring ability, and precise laser projection helps enhance the laser's efficiency.

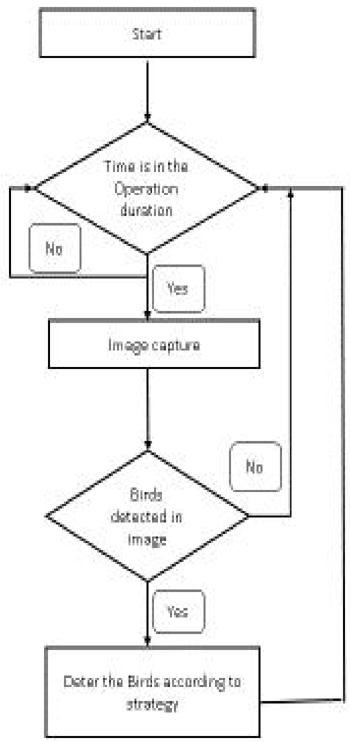

Figure 6-Algorithm of proposed model

Method of Quantification

Previous studies show that observations are made by the farmers to judge the best methods to deter the birds [24]. To guess the number of birds in crop fields, researchers count bird droppings. Skilled experts also use video recordings to count the birds. Many deep learning techniques are used to count the birds, such as Faster RNN and SDD [24]. In this article, a quicker and more balanced method is used to measure the results of bird deterrents. A camera is used in the system, which takes pictures every minute, and then the trained Yolov11 model counts the birds in every picture. By adding up the birds detected in each image, the total birds in the field is estimated easily. This method allowed for quick data analysis without the need for manual counting. Two indicators were used to measure the efficiency proposed system.

1. **Daily Bird Repulsion Rate (BRRd):** This pointer measures how many birds were repelled by the system in a full day. It equates the number of birds when the system is on and when it is off. The system remains on and off for 6 hours. The repellent effect was determined by calculating the difference between these two times.

$$BRRd = \frac{\text{Sum of rate when cam off} - \text{Sum of rate when cam}}{\text{Sum of rate when cam off}} * 100\%$$

2. **Hourly Bird Repulsion Rate (BRRh):** This pointer looks at how effective the system was in repelling birds in just one hour. It equates the number of birds when the system is in operational and non-operational modes in one hour. This helps monitor how well the system works in shorter time frames.

$$BRRh = \frac{\text{Avg time when cam off} - \text{time when cam on}}{\text{Avg time when cam off}} * 100\%$$

Statistical Evaluation

Statistical evaluation is done by taking the results of experiments. To evaluate the efficiency of the system, the observed birds per hour are divided into two groups

1. Treatment group: where the system is turned on.
2. Control group: where the system was turned off.

Performance of the Trained Model

In real-time, the former tells about the birds that are causing loss to their crops based on previous knowledge. The Yolo trained model will detect and deter the birds once the birds are selected. The dataset will consist of several bird pictures for data augmentation to increase the model's performance. The model is trained on the dataset(Bird-feeder) taken from a Robow flow site. In data preprocessing, bird images are loaded as a file

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in the directory. 12% of pictures are taken for testing and validation, and 88% are used for training. Auto-orientation and augmentation are applied to the data. Data augmentation is used to enhance the capacity of training and testing data to increase the performance of deep learning models.

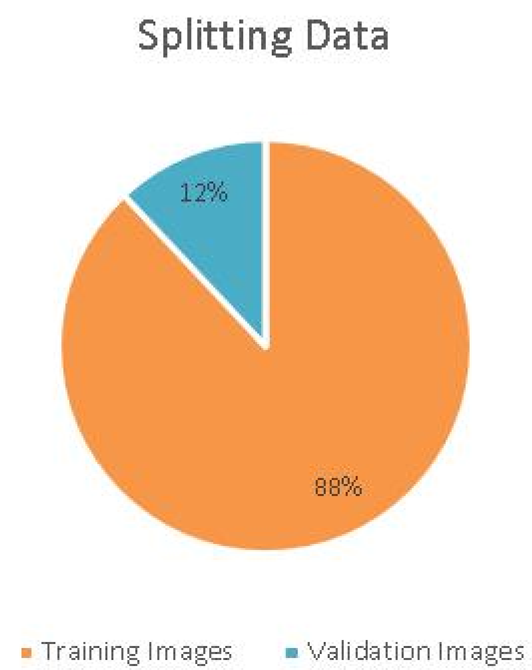

Figure 7: Splitting data

Simulated Training Results

Performance Metrics are essential phases that should be wisely selected based on the established model under deliberation. Several performance metrics are used to measure the predictive power of the model.

Table 1: Performance Metrics

Metric	Formula	Explanation
Precision	$\frac{TP}{TP + FP}$	The correctness of the training can be measured by the Precision of the proposed automatic birds detecting and deterring Model.
Recall	$\frac{TP}{TP + FN}$	Used for classification problems of classes of proposed automatic bird detecting and deterring

		Models.
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$	Used to measure the overall correctness of a classification of proposed automatic bird detection and deterrence Models.
F1-Score	$2 * \frac{Precision * Recall}{Precision + Recall}$	The F1-Score is the harmonic mean of Precision and Recall of the proposed automatic birds detecting and deterring Model.
FNR	$\frac{FP + FN}{TP + TN + FP + FN}$	It tells how the system fails to identify the positive instances of the proposed automatic bird detecting and deterring Model.
TPR	$\frac{TP}{TP + FN}$	Used to measure the positive cases, which are identified by the classification model of the proposed automatic birds detecting and deterring Model.
TNR	$\frac{TN}{TN + FP}$	Used to measure the negative cases, which are identified by the classification model of the proposed automatic birds detecting and deterring Model.

Confusion Matrix

A confusion metric is a tool used for calculating the performance of a classification model by comparing true labels (x-axis) with predicted labels (y-axis). Each cell symbolizes the number of samples classified into specific categories, with diagonal cells indicating correct classifications and off-diagonal cells showing misclassifications. The color bar on the side illustrates the mapping of numbers to color intensity.

Table 2: Confusion Matrix

True \ Predicted	Black Birds	Blue tit	Coal tit	Great tit	House-sparrow
Black Birds	57	0	0	0	0

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Blue tit	1	58	0	0	0
Coal tit	1	1	55	1	0
Great tit	0	2	59	0	0
House-sparrow	1	1	0	0	59
Back-ground	0	0	0	0	1

F1-Confidence Curve

This is a visualization tool used to measure the performance of a classifier through different confidence thresholds. It helps estimate how sound the model balances precision and recall as its confidence in predictions changes.

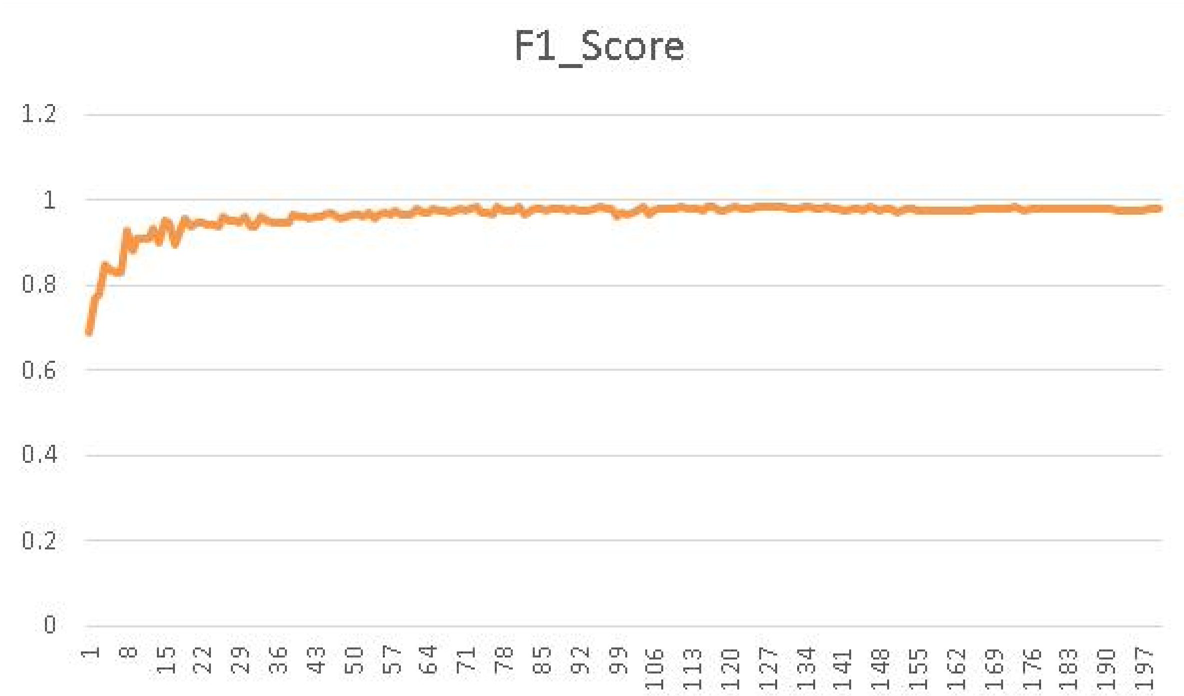

Figure 8-F-1 Confidence Curve

The **F1-Confidence Curve** estimates a classification model's performance across confidence thresholds. The X-axis shows confidence levels (0 to 1), while the y-axis shows the F1-score, balancing precision and recall. Colored lines represent F1 scores for individual classes, with the thick blue line showing the overall average. The model performs well for all classes, and the overall F1-score peaks at 0.98. As confidence

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approaches 1, the F1-score drops sharply due to fewer expectations meeting the threshold. Smooth curves show well-regulated predictions, while sharp variations propose data or classification challenges. To increase performance, focus on optimizing the threshold, addressing class-specific issues, and calibrating the model's confidence scores.

Recall-Confidence Curve

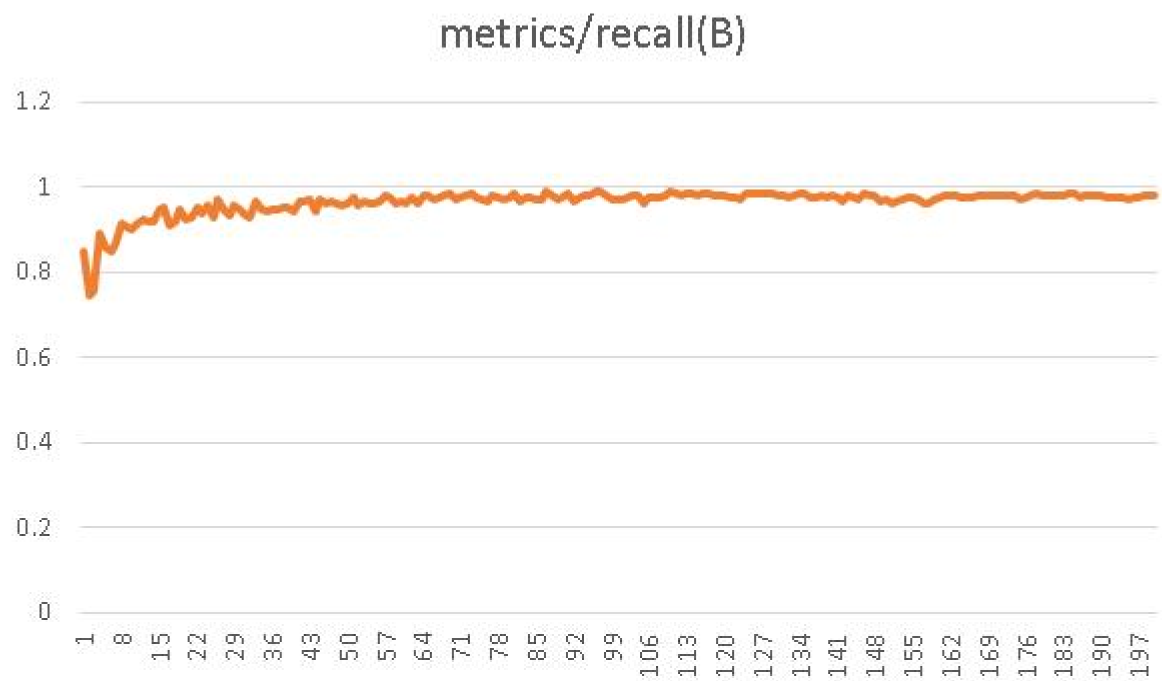

Figure 9-Recall Confidence Curve

The **Recall-Confidence Curve** shows how recall and confidence thresholds differ in a classification model. The horizontal axis shows confidence level (0 to 1), while the vertical axis shows recall, which calculates the proportion of positives correctly recognized. Colored lines show recall for individual classes, and the thick blue line shows the overall average. Recall is maximum at lower confidence thresholds, where most estimations are positive, and falls as the threshold increases, severely constraining the model. To increase the performance, adjust the confidence threshold based on the needed application, increase

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recall for failing classes, and confirm good confidence scores for models.

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Precision-ConfidenceCurve

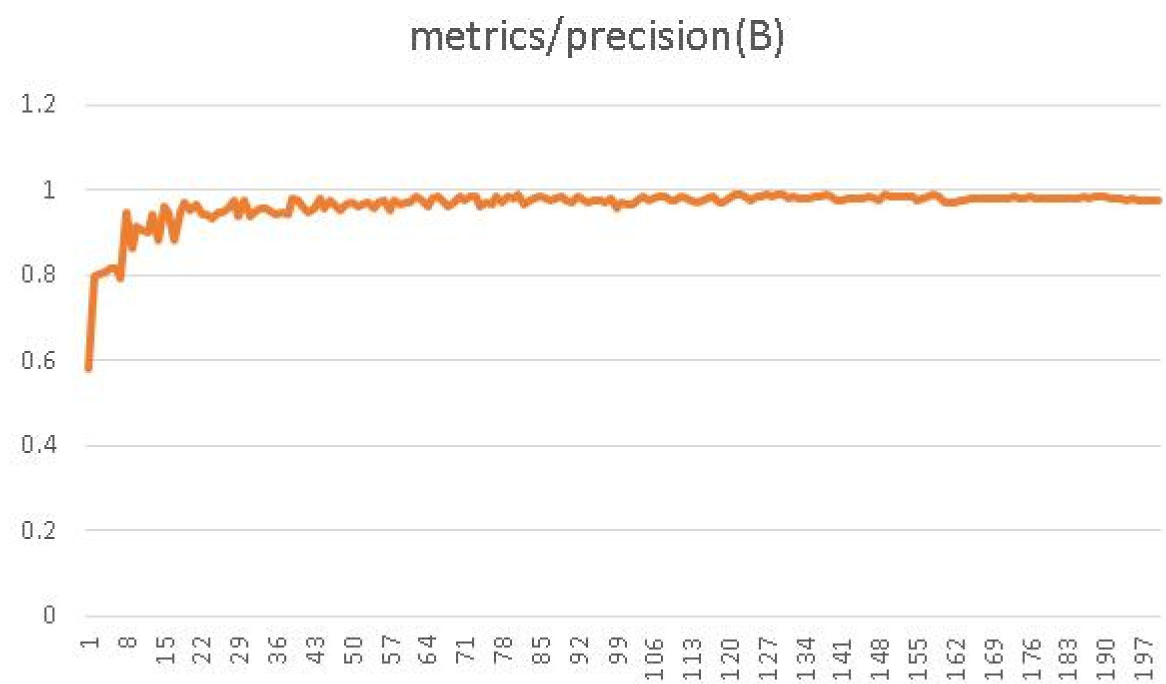

Figure 10-Precision Curve

The **Precision-Confidence Curve** shows how precision alters with confidence thresholds in a classification model. Precision calculates the proportion of positive calculations that are correct, with higher values showing fewer false positives. Each

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class has a corresponding curve, indicating how precision varies as the confidence threshold grows. Precision generally increases with confidence, and the model achieves perfect precision (1.00) at a 1.0 value of confidence threshold through all classes. To get maximum performance, a threshold can be set around 1.0, while efforts to improve precision at lower thresholds for challenging classes can be prioritized. Additionally, balancing precision and recall is vital for applications demanding both accuracy and completeness. Overall, the curve tells about precision and high confidence levels.

Training Metrics

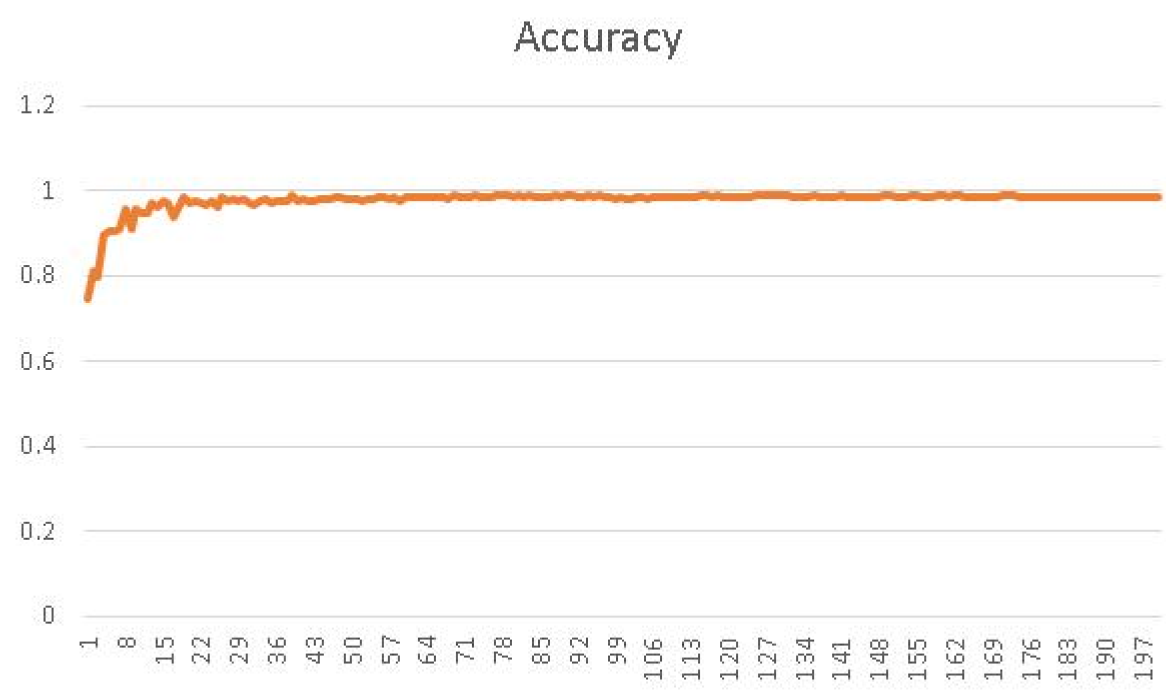

Figure 11-Accuracy curve

This picture covers many plots tracking the training and validation performance of a model with time (likely across epochs). **Training Metrics (Top Row) train/box loss** denotes the training loss related to bounding box regression (important in object

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detection tasks). The curve indicates a constant decline, showing that the model is improving in calculating bounding boxes with time. **Train/cls_loss** shows the training loss for classification (accuracy of predicting the correct class labels). A steady decay advises the best classification performance as training progresses. **Train/dfl_loss** mentions the training loss connected with distribution focal loss (often used in bounding box localization refinement). A related decreasing trend represents that the model is purifying its calculations efficiently. **Metrics/precision(B)**, trails the accuracy of the model during training (proportion of true positive predictions out of all positive predictions). A growing trend shows improved precision with time. **Metrics/recall(B)**, trails the recall during training (proportion of true positives out of all actual positives). An upward trend suggests the model is better at identifying relevant instances. **Validation Metrics (Bottom Row) val/box_loss** calculates the bounding box regression loss on the validation dataset. A declining trend indicates the model's generalization to unobserved data is enlightening. **Val/cls_loss**, validation classification loss, which is decreasing, showing that the model is becoming better at classifying objects on the validation data. **Val/dfl_loss**, similar to the training counterpart but estimated on the validation set. A decay in val/box_loss shows better generalization to undetected data, and an increase in metrics/mAP50(B) suggests upgraded object detection performance at an IoU threshold of 50% on the validation set. **Metrics/mAP50-95(B)**, the metric calculates mAP over a range of IoU thresholds (spanning from 50% to 95%) during validation. The steady rise determines improved detection accuracy over a broader range of IoU thresholds.

Training and Validation Loss:

The graph in Figure 12 shows that both training and validation losses decrease steadily, showing the robustness and generalization of the model.

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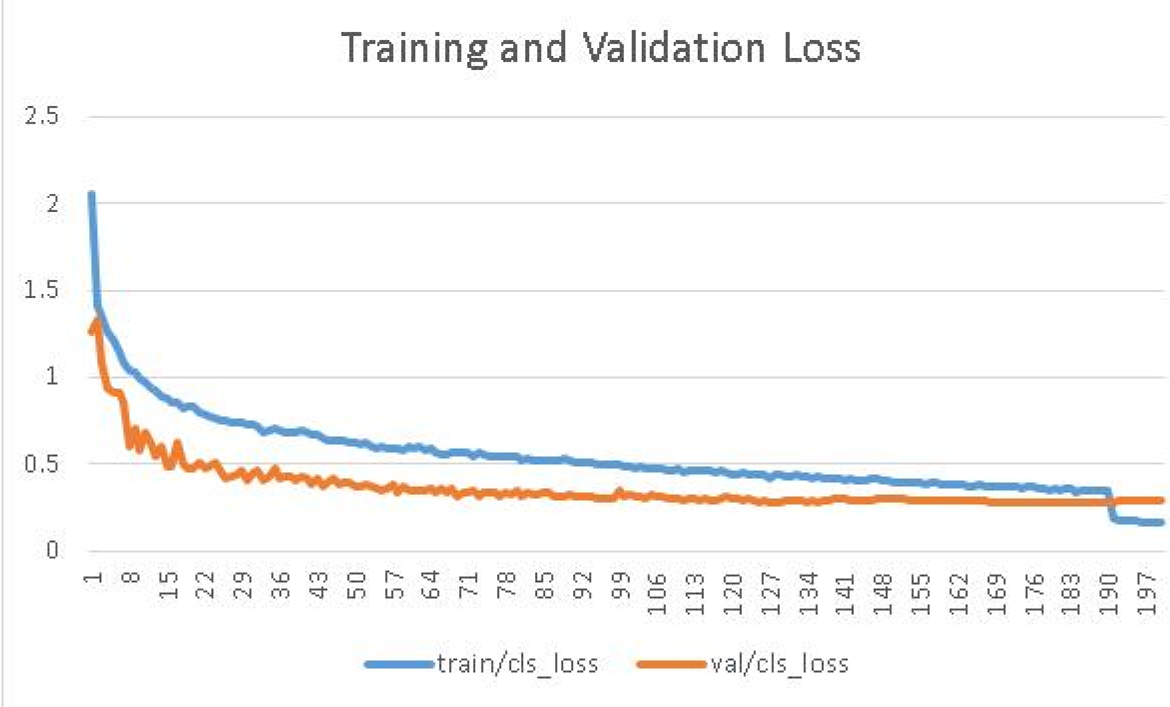

Figure 12: Training and Validation loss curves

Comparison table of different Yolo models on different datasets

Dataset Name	Detection Model	Precision	Recall	mAP@-5%	F-1 Score	Validation Accuracy %
	Yolov3	0.912	0.838	88.9		
	Yolov4	0.86	0.80	87.2		
Cascaded radar ([25])	Yolov5	0.932	0.825	89.9		
Bird-Mix ([26])	Improved Yolov5	0.91	0.848	92.0		
self-built bird dataset [27]	Yolov7			89.6		
Custom dataset([28])	Yolov8	0.85	0.70	80	0.775	
homemade visible light([29])	Yolov9		0.84	63		
Bird-Feeder Our Model	**Yolov11**	**0.9587 (Macro)**	**0.9546 (Macro)**	**96.02**	**96.54 (Macro)**	**96.02**

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Conclusion

Birds play a dual role in agriculture. They often attack the agricultural farms and leading to large financial losses for farmers. Managing bird populations through a combination of deterrents and habitat management is key to minimizing their negative effects. It is also necessary to pay instant attention and take effective solutions to address the harm caused by them. Controlling the birds is important in farming to prevent the loss of food. The proposed system is an automatic deterring system that deters the birds from the crops safely and soundly. This automatic deterring system is used to conserve the Environment without harming the birds. This system uses the deep learning approach YOLOv11, integrated with a rotating laser mechanism to detect and deter the birds from crops. The performance of the proposed system is confirmed by functions such as recall, precision, F1-score, and accuracy. The results of the 'Automatic Detecting and Deterring Birds Integrated with Laser System' model show good accuracy, 96.02% for all categories of birds with metrics/mAP50(B) value of 0.9602 and F-1 value of 96.54. The system is very efficient because it can detect even very small birds. This model can be applied to large-scale data analysis. The system will have proved to be an operative solution for detecting and deterring the birds, offering the potential for broader applications in bird control at various agricultural sites.

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