Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 3, Issue 7, 2025

TRANSFER LEARNING-BASED SMART CROP PROTECTION SYSTEM FOR ANIMAL DETECTION AND DETERRENCE

Gulzar Ahmad[*1], Adeel Khan[2], Muhammad Sajjad[3], Ayesha Saddiqa[4], Muhammad Mudassar Naveed[5], Zaigham Riaz[6]

[*1,2,3,4,5]*School of Computer Sciences, Minhaj University Lahore Punjab, Pakistan*
[6]*National College of Business Administration & Economics, Punjab Pakistan*

[*1]gulzarahmad.cs@mul.edu.pk

DOI: https://doi.org/10.5281/zenodo.16360315

Keywords
Transfer Learning, Artificial Intelligence, Internet of Things (IoT), YOLO, object detection

Article History
Received: 23 April, 2025
Accepted: 08 July, 2025
Published: 23 July, 2025

Corresponding Author: * Gulzar Ahmad

Abstract
Crop depredation by wild and stray animals continues to be a perennial problem in agriculture, resulting in enormous losses in productivity and pressure on the economy of farmers. To overcome this, in this paper, we present a Transfer Learning-Based Smart Crop Protection System based on the YOLO (You Only Look Once) object detection model, for real-time detection and prevention of animal activities. Through the transfer learning of a pre-trained YOLO architecture, the system is trained to detect certain types of animals causing crop damage, even with a small amount of domain-related images. Live video streams obtained from field-mounted cameras are analyzed to estimate the presence of animals with high accuracy and low vibrant. Once detected, the system can automatically initiate nonlethal countermeasures, such as sound alarms or flashing lights tailored to the type of animal identified. The Internet of Things(IoT) and edge computing are incorporated, which facilitates on-site computing without always being connected to the cloud. Experimental results suggest that our system can accurately detect elastic object approximations under different lighting and environment situations, with strong deterrent responses and decreased false positives. The system offers an intelligent and automatic scale value-added crop protection by effectively employing transfer learning and deep learning models. The accuracy of the proposed model in detecting the animal is 93%. This Artificial Intelligence (AI) approach saves the crop from animals.

INTRODUCTION

Agriculture is the central bone of the Pakistani economy. Where 70% population of the country depends upon it directly or indirectly [1]. They need to provide food year to year, increasing population despite a very small area of land. It is expected that in five years shortly that there will be a 15% to 20% increase in feeding items [2]. Although a large number of the population depends upon this field yet they are in an uncertain condition to maintain life in this field now. The cause is that there could be some changes in fields outside or inside. For example, suitable environment, selection of seed, fertilization, input, and irrigation etc.

Today it is another element to destroys crops is the entrance of animals into the fields to fields the dispute between animals and formers is expanding common in the whole country [3]. In forest areas and their related areas, there are many problems and formers have to bear big

ISSN (e) 3007-3138 (p) 3007-312X
Volume 3, Issue 7, 2025

losses. They're using traditional and current methods. They use shotguns, strings, and stones. To overcome these problems electrical wielding machine fence is used but not according to expectations. To save and protect their crops, some efforts have been made for solutions. Machine-learning gives the ideas of the use of IoT, which is its basic solution[4]. IoT controls those things that are linked with it and transforms information on the network by using technology sensors and different electronic components. IoT enables to collection of data in real-time from form fields [5]. In this study, we offer with new conversation service by synchronization of Pi-Camera, LED, and Buzzer with clouds in the field. The exterior part implemented wireless technology, WiFi, to cooperate with information centers through a modern IoT gateway. Pi Camera from field 7/24 is used to capture pictures in real time during the day and night. Through WiFi modules, ESP8266 transforms the parts of hardware parts and uses TCP/IP protocol for the correlation low low-value and easy programming of the controller Raspberry Pi.

Figure 1: Different Animal destroying the crops

Deep learning builds an intelligent model by analyzing a dataset [6]. These models make decisions after recognition of hidden patterns. For object detection and classification model is trained. The system is connected with Twilio Communication API, which is used to communicate with former about the situation. A Raspberry Pi controls the management of the system [7]. This modern technology gives the best solution to prevent crops from animals by giving real-time monitoring and alerts.

Table 1: Percentage of damage produced by the different wild animals

Sr. No	Wild Animal Name	Name-of-the-Crop	Damage in (%)	Reciprocating Action
1	Elephant	Sugarcane, Coconut, plantain, paddy, maize	(72%)	Use Bright Lights, Noise
2	Gaur	Mulberry and sandal	(62%)	High-frequency sound-waves
3	Sambar deer	Pasture, forestry, plantations, gardens	(17%)	Loud noise and dazzling lights
4	Wild boar	Paddy's maize, bean, corn, and fruit trees	(16%)	Loud noise
5	Monkey	Maize, wheat, rice, and vegetable crops	(75%)	Lighting with sound
6	Porcupine	Maize, Potatoes, Groundnuts, Sugarcane	(65%)	Dazzling lights
7	Goral	Maize, Potato, Millet, Wheat, Paddy	(20%)	Loud noise and dazzling lights
8	Bear	Field corn, Oats, and Sweet Corn	(55%)	Fire and Noise
9	Wolf	Rice, Wheat, Maize, Pulses, and Mustard	(18%)	Loud noise and dazzling lights
10	Zebra	Maize or Corn, Potato, Tomato, Carrot, and other Vegetables.	(15%)	Loud noise and dazzling lights

Literature Review:

Deep learning models for detection are divided into two categories: two-stage and one-stage detection algorithms. Two stage involves SPP-Net[7], R-CNN[8], and Faster-RCNN[9]. These models achieve high detection accuracies, but due to the two-stage detection algorithms, they consume more time. In contrast, Yolo model [10] and Center Net [11] are one-stage algorithms. Yolo model especially has high speed and accuracy, and can detect objects and classify them in one shot. But the two-step algorithms first detect the objects and then classify them, consuming a lot of time. Due to speed and high accuracy one one-step algorithms are preferred.

Zhou et al[12] suggested a multi-visual perception method for prominent object detection, motivated by the human visual system's capability to quickly diagnose and concentrate on imposing regions. For remote sensing imagery, Liu et al[13] presented an Adaptive Multi-Scale Feature Enhancement and Fusion Module (ASEM) algorithm, which enhanced object detection performance over fine multi-scale feature fusion, attaining mAP developments on the DOTA-v1.0 (74.21%) and HRSC2016 (84.90%) datasets. Concentrating on unimportant solutions, Yue et al[14] established YOLO-SM, a network intended for single-class multi-deformable targets, maintaining high speed while significantly enhancing accuracy and oversimplification over its DCM module and GMF feature fusion structure.

Other revolutions contain anchor-free methods for precise applications, such as Kim et al.'s [15]. Method for detecting minor faults on apple faces. Additionally, Wang et al[16] suggested a dual-branch structure combining Graph Convolutional Networks (GCN) for universal data detection and Convolutional Neural Networks (CNN) for local feature focus, joined with a dynamic weighted hierarchical loss function, to increase the conduct of cross-domain classification problems.

Current improvements in the YOLO series have also been discovered, with L et al[17] enlightening YOLOv5 over the introduction of an attention mechanism, a bidirectional feature pyramid network, and an EIoU loss function (RSI-YOLO). Also, Han et al[18] planned an end-to-end attention mechanism precisely for crop planning in time-series SAR imagery. While these approaches have proved advancement in addressing numerous object detection issues, including cross-domain challenges, they regularly suffer from boundaries such as reliance on large labeled datasets, high computational resource necessities, and a lack of universality, requiring additional research to overcome these hurdles.

In the agricultural sector, remote sensing image object detection jobs present unique complications. Modern research has focused on these discriminations, including studies on remote sensing image registration[19] and well-organized detection and counting of corn and wheat ears. The latest restatement in the YOLO series has established significant developments in object detection tasks regarding both accuracy and real-time performance[20].

The Proposed Methodology:

Dataset and Resources:

To train and evaluate a Deep-based animal detection model, we collected the label data from Robo-flow, a well-known platform for dataset collection. It gives tools to upload, preprocess, and provides many formats of datasets compatible with Deep learning models. The model contains 10 classes in the datasets, such as Bear, Boar, Crocodile, Elephant, Lion, Monkey, Person, Snake, Tiger, and Wolf. The dataset contains a total of 16968 images. Each image is labeled in the dataset to ensure the quality and correct classification. Robo-flow gives us many preprocessing steps such as image resizing, normalization, and data augmentation 87% of images are used for training, 10% images for validation, and 03% for testing.

Deep Learning Model components and working (YOLOv9 Model):

One of the primary uniqueness lies in the combination of YOLOv9 (You Only Look Once). A front-line deep-learning model for real-time object detection. YOLOv9 has excellent accuracy and is fast, making it a complete option for describing and classifying animals without losing time, and decreasing the detection inactivity necessary for effective determination [21]. YOLOv9 is a single-stage detector that works with two tasks: 1st is the localization, and 2nd is classification in one move through the Network-Architecture [22]. The YOLOv9 algorithm is shortly explained, which contains the following steps:

Grid Division': An input image is separated parts by parts in a fixed-size grid('S*S'), in which every cell is liable for making decisions or forecasts on object localization(bounding box) and classification(Class Probabilities) [23].

Class Prediction And Bounding Box: In this, every cell supposes many bounding boxes, besides box location('x,y'), dimensions('w, h'), and confidence score, and also objects related to a predefined class[24]. **Final Detection:** The algorithm calculates a final and clear score for every bounding box, considering the score of box confidence and probabilities of every class. This results in corresponding overlaying boxes with Up/High and Down/Low-confidence detections[25]. Therefore, an NMS (Non-Maximum Suppression) algorithm is tested to keep the bounding box with the high/up score and delete/eliminate overlapping or down/low-confidence detections. Now the last forecast consists of a bounding-box (x, y, w, h) class labels and Confidence[26].

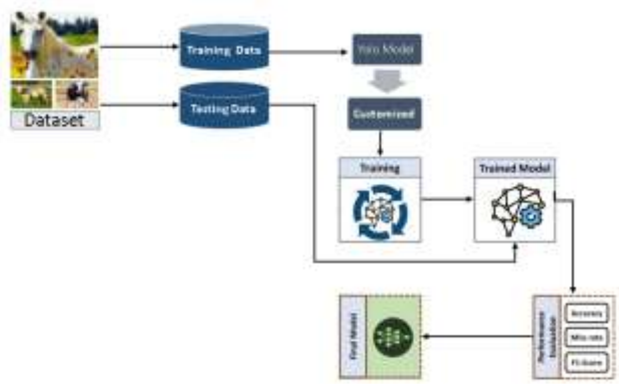

Figure 2: Proposed Deep Learning Model(Yolov9)

The images collected are divided into two parts, training data and testing data. The model is customized to meet the specific requirements. Then it is trained to detect and classify the animals. The performance of the dataset is tested by performance metrics before the deployment in the real world.

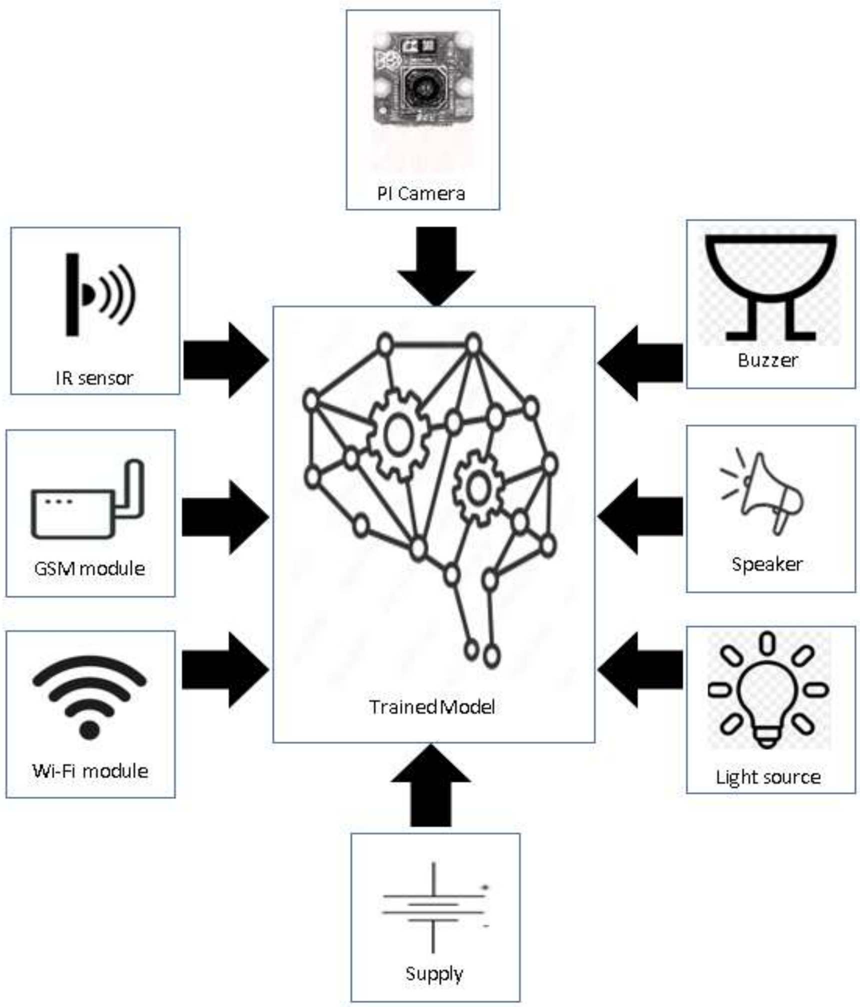

Figure 3: Proposed Complete System Architecture

System Construction and Working:

The system involves the development of a smart crop protection system from animals with the help of deep learning, as shown in the block diagram. We used the battery to power the whole system. The camera module is an interaction with deep transfer learning. An animal is detected in the presence of the crop, and the radar sensor triggers the camera to catch the image. The catch image from the camera is provided to the trained model to determine the type of animal found and the differences between animals and humans. We used the deep learning-based model to examine the animal in the captured image, and if the animal is found or detected, the system will generate a high-frequency Buzzer and also a light strobe. This will drive away the animals from the crop without hurting them. The system is also comprised of a notification system that will send SMS alerts to the Farmer.

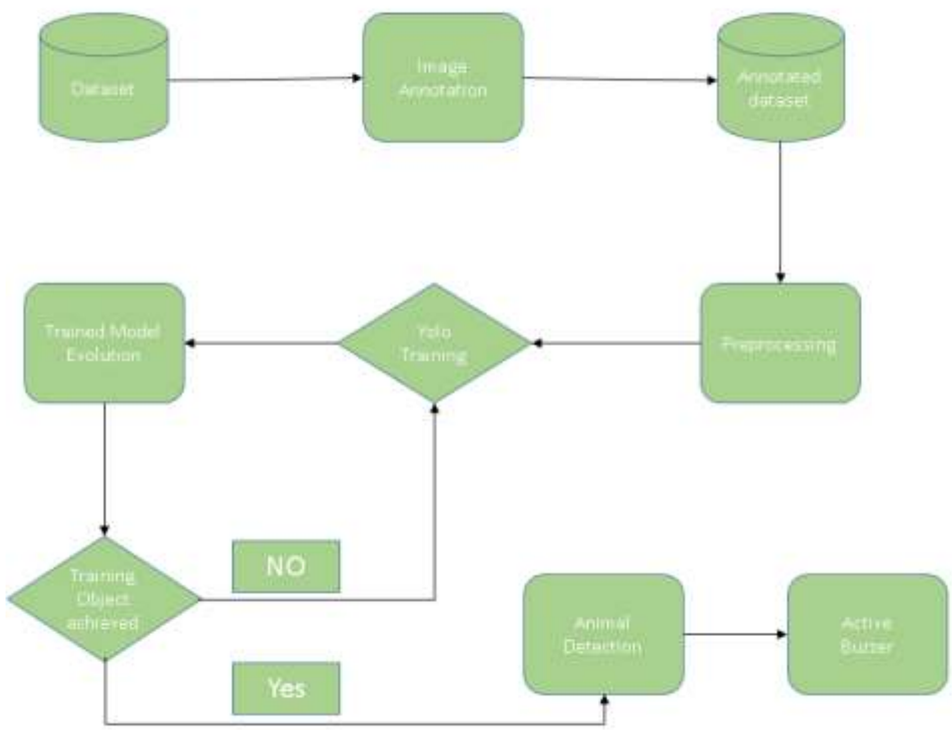

Figure 4:Flow Chart of Proposed Model

Problem Statement:

A lot of farmers in Pakistan use electric bars/fences to protect their crops from animals [27]. However, this system has many problems, like sometimes voltage drops arise and the owner of the electrical bar has to examine the voltage; however, unable to know it without reality going there, and This system hurts the animals. The other running system mostly allows/produces control functionality [28]. Also, the above-mentioned systems don't give crop protection from animals, particularly in above mentioned application area. They along with required to take actions based on the kind of animals that attempt to enter the crops, as distinct methods are used to prevent distinct animals from entering related blocked areas[29]. The other typically used manner by the farmers in the plan/structure is to stop crop destruction by animals. Consists of construction physical hurdles, use of electric bars, manual supervision, and many similar weak and unsafe methods [30].

We are going to develop a system that detects the animals without any human involvement. We install it in crop fields without physical or manual security.

Performance Evaluation:
This is measured by the metrics given in the table below. These metrics tell how well the model is working. These metrics are used to judge the performance of the model. **Table 2 Performance Metrics** [31]**:**

Table 2:Performance Metrics

Matric	Formula	Explanation
Precision	$\frac{TP}{TP+FP}$	The precision is a number that shows the number of information digits, and it expresses the value of the number.
Recall	$\frac{TP}{TP+FN}$	In the proposed Model, the recall is computed by the True Positives of all pest datasets, divided by the sum of True Positives and False Negatives.
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	Accuracy shows the percentage of true predictions and is calculated as the sum of True Positive and True Negative divided by the sum of True Positive, True Negative, False Positive, and False Negative.
F1-Score	$2*\frac{Precision*Recall}{Precision+Recall}$	The F1-score is calculated by multiplying Precision and Recall by 2, then dividing by the total of Precision and Recall.
FNR	$\frac{FP+FN}{TP+TN+FP+FN}$	The False Negative Rate of the proposed model is derived by taking the total of False Positives and False Negatives and dividing by the total of True Positives, True Negatives, False Positives, and False Negatives.
TPR	$\frac{TP}{TP+FN}$	The True Positive Rate is calculated in the proposed model by dividing the True Positive of all pest datasets by the sum of the True Positive and False Negative.
TNR	$\frac{TN}{TN+FP}$	The proposed model calculates the True Negative Rate by dividing the test dataset's True negatives by the total of True Negatives and False Positives.

Dataset Distribution Overview
The dataset contains 10 distinct classes: **bear, boar, crocodile, elephant, lion, monkey, person, snake, tiger, and wolf**. The number of instances in each category differs slightly, showing a **nearly balanced dataset**; however, some categories hold more samples than others.
Elephant has the highest number of instances with **2,500 samples**, making it the most significant class in the dataset. **Boar**, **monkey**, and **snake** follow closely with **2,000**, **2,020**, and **2,010** instances, respectively. **Tiger** and **bear** also have a substantial number of instances, with **1,990** and **1,950** samples each. **Lion** shares the same count as the **bear**, at **1,950**. **Wolf** and **crocodile** have the lowest number of instances among the animal classes, each with **1,850** samples. **Person** class has **1,880** instances, which is slightly lower than most animal categories.

Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 7, 2025

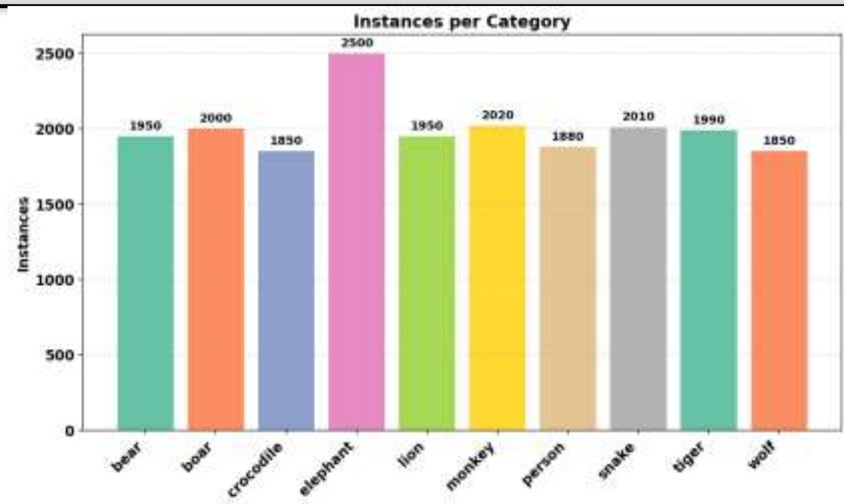

Figure 5:**Dataset Distribution**

Confusion Matrix:
An algorithm for the performance visualization that is laid out in table format is called a confusion Matrix. It is fruitful to measure Accuracy, Specificity, Recall, Precision, and most importantly is AUC-ROC Curve.

Table 3:Confusion Metrix

		Predicted Values										
	N=1871	Bear	Boar	Crocodile	Elephant	Lion	Monkey	Person	Snake	Tiger	Wolf	Total
True Values	Bear	161	2	3	5	0	7	2	0	1	1	**182**
	Boar	1	230	0	0	1	0	0	0	0	0	**232**
	Crocodile	0	0	163	0	0	0	1	1	1	0	**166**
	Elephant	0	1	1	196	0	0	0	1	0	0	**199**
	Lion	2	0	0	0	170	4	0	1	1	1	**179**
	Monkey	0	0	0	1	4	171	0	0	0	2	**178**
	Person	2	0	1	0	0	0	164	0	0	1	**168**
	Snake	0	0	2	1	0	0	1	174	0	0	**178**
	Tiger	1	0	1	0	1	0	0	0	166	0	**169**
	Wolf	10	2	1	1	0	3	0	0	0	203	**220**
	Total	**177**	**235**	**172**	**204**	**176**	**185**	**168**	**177**	**169**	**208**	**1871**

The confusion matrix visualizes the performance of the classification model by comparing Training **& Validation Metrics.**

- Total **Samples: 1871**
- Most classes are **highly accurately predicted**, showing good model performance.
- The **Boar, Elephant, and Crocodile** classes have the **highest accuracy**, with minor misclassifications.
- Slight confusion is observed between:

- **Bear vs Monkey/Wolf**
- **Lion vs Monkey**
- **Snake vs Crocodile**
- **Wolf vs Bear/Monkey**

Model Performance Analysis:

The classification model was calculated on a dataset comprising 1,871 total samples, ranging across ten different animal and human classes such as Bear, Boar, Crocodile, Elephant, Lion, Monkey, Person, Snake, Tiger, and Wolf. The calculation was based on standard performance metrics: **Precision, Recall, and F1-Score**, calculated for each class exclusively.

Table 4:Model Performance Analysis

Class	Accuracy	Miss Rate	Precision	Recall	F1-Score
Bear	88.5%	11.5%	91.0%	88.5%	89.7%
Boar	99.1%	0.9%	97.9%	99.1%	98.5%
Crocodile	98.2%	1.8%	94.8%	98.2%	96.4%
Elephant	98.5%	1.5%	96.1%	98.5%	97.3%
Lion	95.0%	5.0%	96.6%	95.0%	95.8%
Monkey	96.1%	3.9%	92.4%	96.1%	94.2%
Person	97.6%	2.4%	97.6%	97.6%	97.6%
Snake	97.8%	2.2%	98.3%	97.8%	98.0%
Tiger	98.2%	1.8%	98.2%	98.2%	98.2%
Wolf	92.3%	7.7%	97.6%	92.3%	94.9%

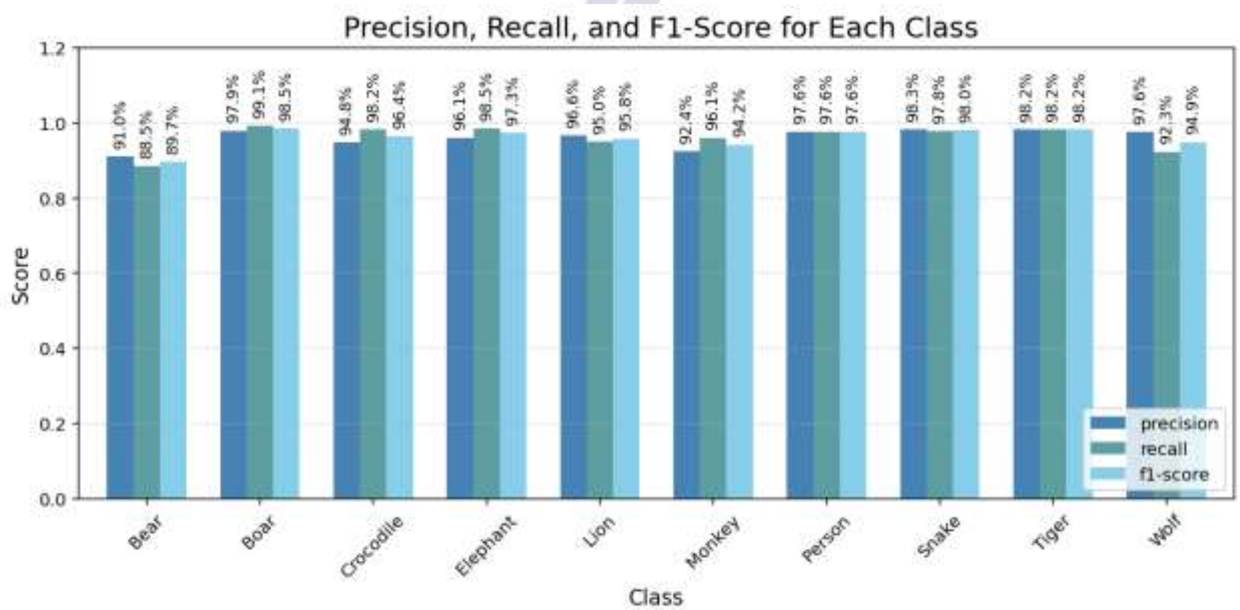

Table 5: Model Performance Metrics Graphs

From the table and graph, it is clear that the model correctly detects 161bear images out of 182 images, resulting in a recall of **88.46%**. It predicted 177 instances as Bear, of which 161 were correct, leading to a precision of **90.96%**. The corresponding F1-score, which balances precision and recall, is **89.70%**, indicating good but not perfect performance. Errors occurred primarily by misclassifying a limited bear as a monkey or a wolf.

The Boar class attained near-perfect performance, with **230 correct predictions** out of 232, giving a recall of **99.13%**. With only five incorrect predictions as Boar, its precision reached **97.87%**.

The **F1-score** was **98.50%**, reflecting high consistency in classifying Boars. For Crocodiles, the model attained **163 correct identifications out of 166** (recall: **98.19%**) and misclassified a few other classes as crocodiles (FP = 9), resulting in **94.74% precision**. The overall **F1-score** was **96.44%**, showing consistent model performance. The Elephant class was also predicted with high confidence. **196 out of 199** were correctly identified (recall: **98.49%**), with a precision of **96.08%**, as only a few misclassifications were made. The **F1-score** stood at **97.27%**, showing excellent model accuracy. The model attained **170 correct predictions** for Lions (recall: **94.97%**) out of 179 actual cases, with a **precision** of **96.59%**, due to six false positives. The F1-score for Lion was **95.77%**. For Monkeys, the model verified **171 true positives**, resulting in a **recall of 96.07%** and a **precision of 92.43%**, slightly lower due to 14 false positives. The **F1-score** was **94.21%**, indicating good but improvable performance. The Person class was highly accurate, with 164 correct predictions out of 168 and only four errors both ways. This gives both precision and recall of 97.62%, and hence a strong F1-score of 97.62% as well. The Snake class was one of the best-performing, with a precision of 98.30% and recall of 97.75%, resulting in an **F1-score of 98.02%**. Only minor misclassifications occurred. The model recognized Tigers with almost perfect accuracy. Out of 169 actual Tiger images, 166 were correctly classified. The model's **precision was 98.21%**, and **recall was 98.24%**, giving an **F1-score of 98.22%**. For Wolves, the model correctly predicted 203 out of 220 (recall: **92.27%**), and made only five false positive predictions, resulting in **97.60% precision**. The **F1-score** was **94.87%**, indicating that while the model is very precise, it missed some Wolves (false negatives). The system performs best, achieving **96.1% accuracy.**

Table 6: Comparison of Results on Different Yolo Models

S.No	Model Name	Validation Accuracy	mAp50	Precision	Recall
1	YOLOv8[35]		0.93	0.93	0.85
2	Yolo-NAS[35]		0.93	0.52	0.98
3	Fast-RNN[35]		0.91	0.85	0.91
4	**Our Proposed Model**	**96.1%**	**95.05**	**96.05**	**96.13**

Conclusion:

Agriculture always remains a vital part of the economy because many people depend on agriculture. Many people use electric fences, artificial repellents, and acoustic systems to protect crops from wild animals, but do not get reliable results. However, agriculture is facing continuous challenges due to many reasons. The proposed approach uses real-time image detection, utilizing models Deep Yolov9 model for accurate and quick detection. This technology will notify authorities in real time and help reduce animal mishaps and conflicts, giving an optimal solution. It aims to protect crops from wild animals. In conclusion. The proposed surveillance system explains the best use of AI and IoT in solving agricultural problems. It offers a scalable, low-cost, and efficient method.

References:

[1] S. Giordano, I. Seitanidis, M. Ojo, D. Adami, and F. Vignoli, "IoT solutions for crop protection against wild animal attacks," *2018 IEEE Int.. Conf. Environ. Eng. EE 2018 - Proc.*, pp. 1–5, 2018, doi: 10.1109/EE1.2018.8385275.

[2] S. H., S. Rao, P. C., and C. N. G, "Survivalence of Rouge Wild Animals Using Image Processing and IOT," in *2019 1st International Conference on Advances in Information Technology (ICAIT)*, 2019, pp. 540–543. doi: 10.1109/ICAIT47043.2019.8987324.

[3] T. Nadu, A. Pradesh, A. Pradesh, G. Lecturer, and T. Nadu, "Eco-Friendly Crops Protection From Damage Caused By Birds Using ML," vol. 20, no. 20, pp. 3075–3086, 2022, doi: 10.48047/NQ.2022.20.20.NQ109305.

[4] K. Yodha, D. Singh, A. Kour, R. Yadav, P. Dahiya, and R. Kumar, "Estimation of Predatory Bird Damage to Winter Guava Crop," *Indian J. Ecol.*, no. January 2024, 2023, doi: 10.55362/ije/2023/4138.

[5] P. Subedi, R. Joshi, B. Poudel, and S. Lamichhane, "Status of Human-Wildlife Conflict and Assessment of Crop Damage by Wild Animals in Buffer Zone Area of Banke National Park, Nepal," *Asian J. Conserv. Biol.*, vol. 9, no. 2, pp. 196–206, 2020.

[6] S. Sreenivas, "Deep Learning-Based Cultivation Protection From Animals With Repellents," no. 11, pp. 10340–10346, 2023.

[7] P. Purkait, C. Zhao, and C. Zach, "SPP-Net: Deep Absolute Pose Regression with Synthetic Views," 2017, [Online]. Available: http://arxiv.org/abs/1712.03452

[8] G. Gkioxari, B. Hariharan, R. Girshick, and J. Malik, "R-CNNs for Pose Estimation and Action Detection," pp. 1–8, 2014, [Online]. Available: http://arxiv.org/abs/1406.5212

[9] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 6, pp. 1137–1149, 2017, doi: 10.1109/TPAMI.2016.2577031.

[10] V. Abhyankar and R. Kene, "Generation of RBC, WBC Subtype, and Platelet Count Report Using YOLO".

[11] R. Rilling, "EnterNet," *Soziol. Ausflüge*, pp. 239–272, 1996, doi: 10.1007/978-3-322-87289-0_22.

[12] W. Zhou *et al.*, "Salient Object Detection via Fusion of Multi-Visual Perception," *Appl. Sci.*, vol. 14, no. 8, pp. 1–18, 2024, doi: 10.3390/app14083433.

[13] W. Liu, G. Ren, R. Yu, S. Guo, J. Zhu, and L. Zhang, "Image-Adaptive YOLO for Object Detection in Adverse Weather Conditions," *Proc. 36th AAAI Conf. Artif. Intell. AAAI 2022*, vol. 36, pp. 1792–1800, 2022, doi: 10.1609/aaai.v36i2.20072.

[14] X. Yue and L. Meng, "Yolo-sm: A lightweight single-class multi-deformation object detection network," *IEEE Trans. Emerg. Top. Comput. Intell.*, 2024.

[15] J. Kim, J. Lee, B. Ngoc, H. Nguyen, J. Lee, and J. Kim, "HAFREE : A heatmap-based anchor-free detector for apple defects HAFREE : A heatmap-based anchor-free detector for apple defects" 2024.

[16] C. Wang *et al.*, "GCFC: Graph Convolutional Fusion CNN Network for Cross-Domain Zero-Shot Extraction of Winter Wheat Map," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, 2024.

[17] Q. Fan, Y. Li, M. Deveci, K. Zhong, and S. Kadry, "LUD-YOLO: A novel lightweight object detection network for unmanned aerial vehicle," *Inf. Sci. (Ny).*, vol. 686, no. March 2024, p. 121366, 2025, doi: 10.1016/j.ins.2024.121366.

[18] Z. Han, C. Zhang, L. Gao, Z. Zeng, B. Zhang, and P. M. Atkinson, "Spatio-temporal multi-level attention crop mapping method using time-series SAR imagery," *ISPRS J. Photogramm. Remote Sens.*, vol. 206, pp. 293–310, 2023.

[19] H. Zhou *et al.*, "Feature matching for remote sensing image registration via manifold regularization," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 13, pp. 4564–4574, 2020.

[20] Z. Yu, J. Ye, C. Li, H. Zhou, and X. Li, "TasselLFANet: a novel lightweight multi-branch feature aggregation neural network for high-throughput image-based maize tassels detection and counting," *Front. Plant Sci.*, vol. 14, p. 1158940, 2023.

[21] C. V. Narayana, K. Vamsi, P. Pallavi, and G. Dedeepya, *Animal Deterrance using Computer Vision and Raspberry Pi*, no. Icciet. Atlantis Press International BV, 2024. doi: 10.2991/978-94-6463-471-6_73.

[22] P. R. Dhital, "Smart Farming for Farm Security : Mitigate Wild-Birds Intrusion in Agriculture Farms," vol. 4, pp. 209–216, 2025.

[23] Y. Lei *et al.*, "Development of a Slow Loris Computer Vision Detection Model," *Animals*, vol. 12, no. 12, pp. 1–13, 2022, doi: 10.3390/ani12121553.

[24] H. M. Faisal *et al.*, "Detection of cotton crop diseases using customized deep learning model," *Sci. Rep.*., vol. 15, no. 1, pp. 1–19, 2025, doi: 10.1038/s41598-025-94636-4.

[25] V. Bapat, P. Kale, V. Shinde, N. Deshpande, and A. Shaligram, "WSN application for crop protection to divert animal intrusions in the agricultural land," *Comput. Electron. Agric.*, vol. 133, pp. 88–96, 2017, doi: https://doi.org/10.1016/j.compag.2016.12.007.

[26] D. Lu and Y. Wang, "MAR-YOLOv9: A multi-dataset object detection method for agricultural fields based on YOLOv9," *PLoS One*, vol. 19, no. 10 October, pp. 1–22, 2024, doi: 10.1371/journal.pone.0307643.

[27] K. Kaličanin, M. Čolović, A. Njeguš, and V. Mitić, "Benefits of Artificial Intelligence and Machine Learning in Marketing," pp. 472–477, 2019, doi: 10.15308/sinteza-2019-472-477.

[28] A. Eklund, J. Månsson, and J. Frank, "How effective are interventions to reduce damage to crops from herbivorous wild birds and mammals ? A systematic review protocol," *Environ. Evid.*, pp. 1–7, 2023, doi: 10.1186/s13750-023-00315-0.

[29] A. Katharria, K. Rajwar, M. Pant, and K. Deep, "Pr ep rin t n ot pe er r we d Pr ep rin t n er we," 2025.

[30] R. Nikhil, A. B S, and R. P., *Real-Time Monitoring of Agricultural Land with Crop Prediction and Animal Intrusion Prevention using Internet of Things and Machine Learning at Edge*. 2020. doi: 10.1109/CONECCT50063.2020.9198508.

[31] S. K. Roy, A. Roy, S. Misra, N. S. Raghuwanshi, and M. S. Obaidat, "AID: A prototype for Agricultural Intrusion Detection using Wireless Sensor Network," in *2015 IEEE International Conference on Communications (ICC)*, 2015, pp. 7059–7064. doi: 10.1109/ICC.2015.7249452.

[32] F. Hernadi, "Automated Bird Deterrent System : A Review," vol. 07, no. 1, pp. 1–9, 2025.

[33] P. Marichamy, P. Karuppasamy, B. Heera, R. L. Keresi, and M. Kanagalakshmi, "Crop protection from animals based on machine learning," *E3S Web Conf.*, vol. 399, pp. 1–7, 2023, doi: 10.1051/e3sconf/202339904018.

[34] K. K. Iniyaa, J. K. Divya, S. Devdharshini, and R. Sangeethapriya, "Crop protection from animals using deep learning," *Int. J. Progress. Res. Sci. Eng.*, vol. 2, no. 3, pp. 41–44, 2021.

[35] A. Korkmaz, M. T. Agdas, S. Kosunalp, T. Iliev, and I. Stoyanov, "Detection of Threats to Farm Animals Using Deep Learning Models: A Comparative Study," *Appl. Sci.*, vol. 14, no. 14, 2024, doi: 10.3390/app14146098.