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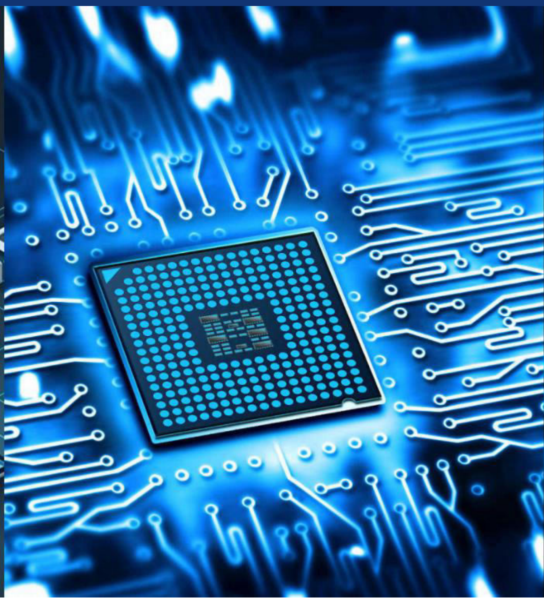

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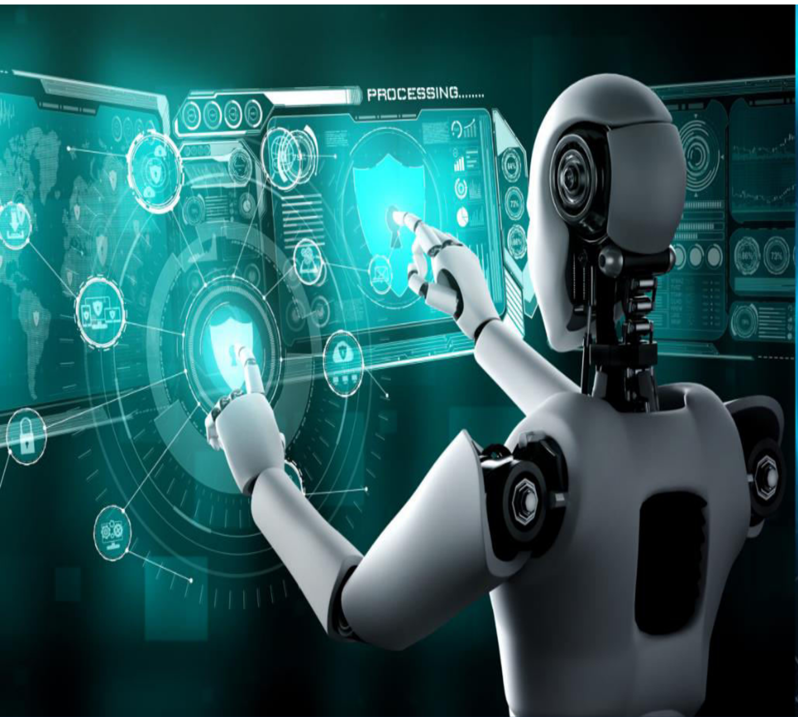

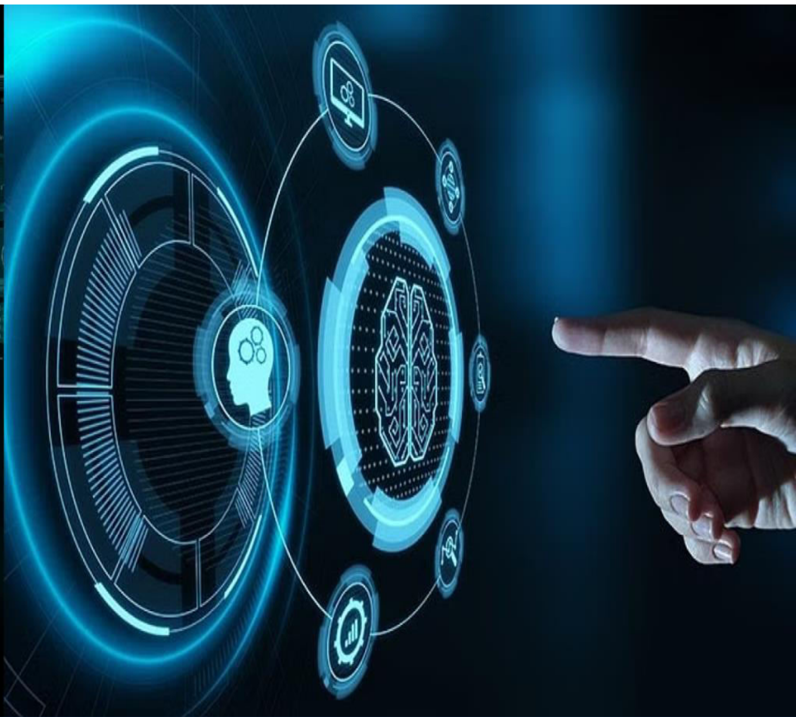

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Animal Intrusion Detection for Agricultural Monitoring using YOLOv8n Object Detection

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ABSTRACT: Animal intrusion causes significant crop damage and economic losses in agricultural regions. This paper presents an animal intrusion detection system based on the YOLOv8n object detection model. A custom dataset containing four animal classes—wild boar, elephant, cattle, and buffalo—was collected, annotated, and used for training and evaluation. Data preprocessing and augmentation techniques were applied to improve model performance and generalization. Experimental results achieved an overall mAP@0.5 of 90.59%, with the highest average precision obtained for elephant (93.4%) and wild boar (92.0%) classes. The results indicate that the proposed approach can effectively detect animals in agricultural monitoring scenarios and may support future intrusion alert systems.

KEYWORDS: YOLOv8n, Animal Intrusion Detection, Agricultural Monitoring, Object Detection, Deep Learning, Computer Vision, Farmland Protection

I. INTRODUCTION

Animal intrusion is one of the common problems faced in agricultural areas. Animals such as wild boars and elephants frequently enter farmlands in search of food and water, causing crop damage and economic losses to farmers. In many regions, domestic animals such as cattle and buffaloes can also enter cultivated fields and affect agricultural productivity. Continuous monitoring of large agricultural areas is difficult and often requires significant human effort. Therefore, there is a need for automated systems that can help detect animals and support agricultural monitoring and crop protection.

Recent advances in computer vision and deep learning have made automated object detection more accurate and practical. Deep learning models, especially Convolutional Neural Networks (CNNs), have shown better performance than many traditional image processing approaches in object recognition and detection tasks. Object detection models can identify and locate multiple objects within an image, making them suitable for real-time monitoring applications.

Several studies have explored the use of deep learning techniques for wildlife monitoring and animal detection. Among the available object detection models, the YOLO (You Only Look Once) family has gained significant attention because of its ability to provide fast and accurate detection. YOLO-based models have been successfully applied in applications such as wildlife monitoring, surveillance, traffic analysis, and agricultural automation.

In this work, an animal intrusion detection system based on the YOLOv8n object detection model is proposed. A custom dataset containing four animal classes – wild boar, elephant, cattle, and buffalo – was collected and annotated for training and evaluation. Data preprocessing and augmentation techniques were applied to improve the quality of the dataset and enhance model performance. The objective of this work is to develop a lightweight and accurate animal detection system that can support agricultural monitoring and help identify animal intrusions in farmland areas.

The experimental results show that the proposed system can detect the selected animal classes with good accuracy, achieving an overall mAP@0.5 of 90.59%. These results indicate that YOLOv8n can be effectively used for animal intrusion detection in agricultural environments.

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II. RELATED WORK

Several researchers have explored the use of computer vision and deep learning techniques for wildlife monitoring and animal intrusion detection. Recent studies show that YOLO-based object detection models provide a good balance between detection accuracy and processing speed, making them suitable for agricultural monitoring applications.

Mamat et al. proposed an animal intrusion detection system for farming areas using the YOLOv5 model. Their work focused on detecting animals commonly involved in farm intrusion and demonstrated that deep learning-based object detection can achieve high detection performance for agricultural applications. The study highlighted the potential of YOLO models for reducing crop losses caused by animal intrusion.

Ibraheam et al. developed an animal species detection system for embedded devices using a modified YOLOv2 architecture with deformable convolutional layers. Their approach improved both detection accuracy and processing speed compared to the original YOLOv2 model. The study emphasized the importance of lightweight and efficient models for practical deployment on resource-constrained systems.

Reddy et al. presented an Edge AI and IoT-based framework for protecting agricultural fields from wildlife threats. The proposed system combined deep learning, edge computing, and IoT technologies to detect animal intrusion and support crop protection. Their work demonstrated the growing role of intelligent monitoring systems in modern agriculture.

Chappidi and Sundaram proposed a wildlife animal detection system based on cascaded YOLOv8. Their approach incorporated image preprocessing, segmentation, and feature extraction techniques before object detection. The study reported strong detection performance and showed the effectiveness of YOLOv8-based architectures for wildlife monitoring applications.

Although previous studies have achieved promising results, many of them focus on specific animal categories, embedded deployment, or integrated IoT-based systems. In addition, the datasets used in different studies vary considerably in terms of animal classes and environmental conditions. Motivated by these observations, the present work develops an animal intrusion detection system using YOLOv8n trained on a custom dataset containing wild boar, elephant, cattle, and buffalo classes. The objective is to provide accurate detection while maintaining a lightweight model suitable for future agricultural monitoring applications.

III. METHODOLOGY

The proposed animal intrusion detection system was developed using the YOLOv8n object detection model. The methodology adopted in this work consists of system design, dataset preparation, image preprocessing, model training, and performance evaluation. The overall architecture and workflow of the proposed system are shown in Figure 1 and Figure 2, respectively.

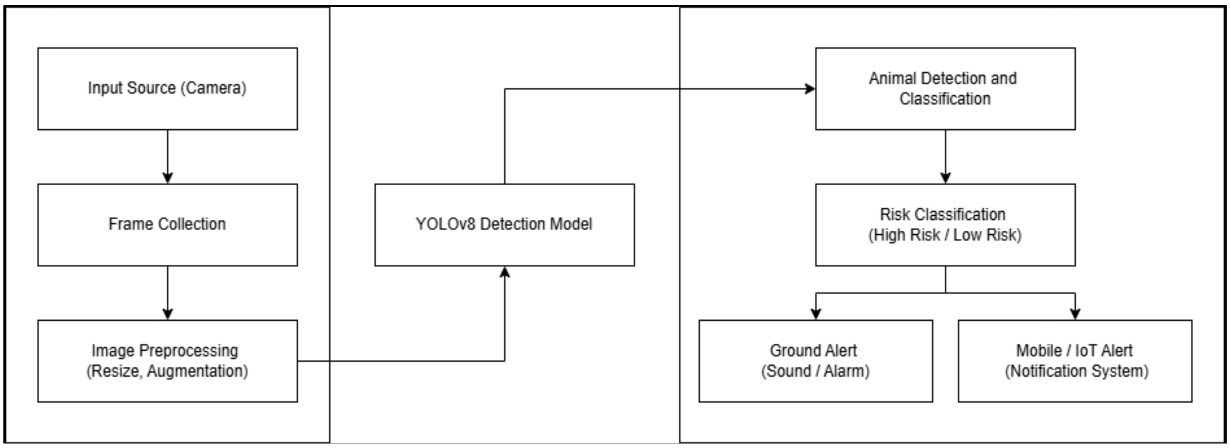

Figure 1

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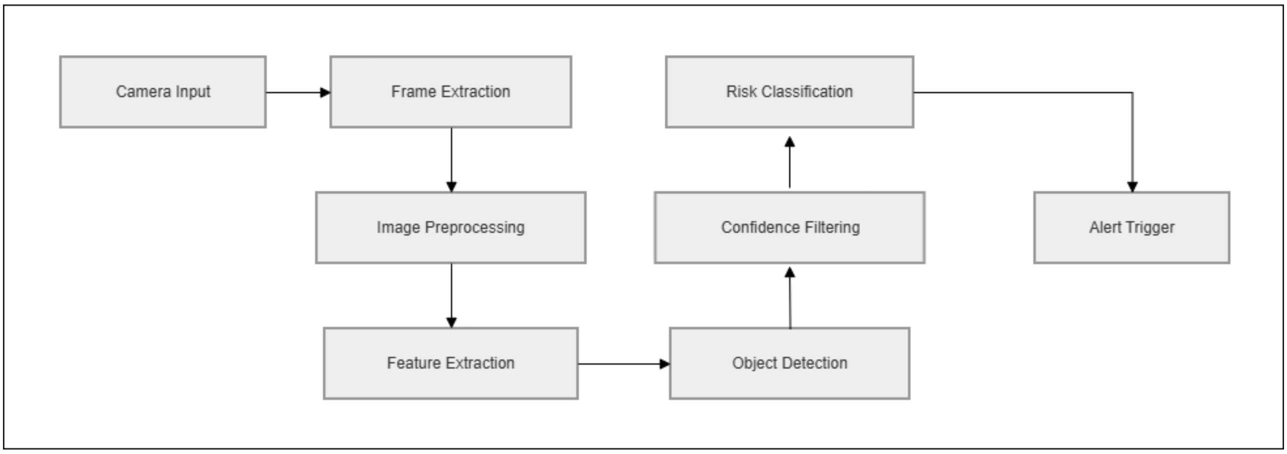

Figure 2

A. System overview

The proposed system is designed to automatically detect animals present in agricultural environments using deep learning-based object detection. Images containing animals are provided as input to the trained YOLOv8n model. The model processes the input image and predicts the location and category of each detected animal by generating bounding boxes, class labels, and confidence scores.

The system focuses on four animal classes: Wild Boar, Elephant, Cattle, and Buffalo. Wild Boars and Elephants were considered primary intrusion classes due to their potential to cause severe crop damage, while Cattle and Buffalo were included to improve the model's ability to distinguish between visually similar animal species commonly found near farmlands.

The workflow begins with dataset collection and annotation, followed by preprocessing and model training. After training, the model is evaluated using standard object detection metrics to assess its detection performance.

B. Dataset collection and annotation

The quality and diversity of the dataset play an important role in the performance of deep learning models. For this work, a custom dataset was prepared consisting of four animal classes: Wild Boar, Elephant, Cattle, and Buffalo.

Images were collected from publicly available sources, including Pixabay, Microsoft COCO Dataset, Open Images Dataset, and the iNaturalist Dataset. Images from these sources were selected to include different poses, scales, backgrounds, and viewpoints of the target animals. The collected images were manually reviewed and organized into their respective classes. Each image was annotated using bounding boxes to identify the location of animals within the image. The annotations were stored in YOLO format, where each object is represented by a class label and normalized bounding box coordinates.

The final dataset consisted of 8,426 annotated images distributed across four animal classes, as shown in Table 1.

Table 1

Animal Class	**Number of Images**
Wild Boar	2559
Elephant	1991
Cattle	1915
Buffalo	1961
Total	8426

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To ensure reliable model evaluation, the dataset was divided into training, validation, and testing subsets using an approximate ratio of 70:20:10.

C. Data preprocessing and augmentation

Before training, all images were resized to 512 × 512 pixels to provide a consistent input size for the model. Standardizing image dimensions improves training efficiency and ensures uniform feature extraction throughout the dataset.

Data augmentation techniques available within the YOLOv8 training pipeline were applied during training to improve model generalization and reduce overfitting. These augmentations introduce controlled variations in the training samples while preserving the important visual characteristics of the animals.

Since augmentation was applied during the training stage, the original dataset remained unchanged and the train-validation-test split was preserved. These preprocessing steps help the model learn more robust features and improve its ability to detect animals in previously unseen images.

D. Yolov8n model and training

YOLO (You Only Look Once) is a single-stage object detection framework that performs object localization and classification simultaneously. Unlike traditional two-stage detectors, YOLO predicts object locations and class labels in a single forward pass, resulting in faster detection speed while maintaining good accuracy.

In this work, YOLOv8n was selected because it provides a suitable balance between accuracy and computational efficiency. As the lightweight variant of the YOLOv8 family, it requires fewer computational resources while still delivering strong object detection performance.

The model was trained using the Ultralytics YOLOv8 framework. During training, the network learned to identify and localize the four selected animal classes from the annotated dataset.

Training was performed on a system equipped with an Intel Core i5-12450H processor, NVIDIA RTX 3050 GPU with 4 GB VRAM, and 16 GB RAM. The training configuration used in this work is summarized in Table 2.

Table 2

Parameter	**Value**
Model	YOLOv8n
Image Size	512*512
Batch Size	32
Epochs	200
Early Stopping Patience	20
Dataset Size	8426 Images
GPU	NVIDIA RTX 3050 (4 GB)
RAM	16 GB

During training, validation data was used to monitor model performance after each epoch. The model weights corresponding to the best validation performance were selected for final testing and evaluation.

E. Performance evaluation metrics

The trained model was evaluated using standard object detection metrics, including Precision, Recall, Intersection over Union (IoU), and mean Average Precision (mAP).

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Intersection over Union (IoU) measures the overlap between the predicted bounding box and the ground truth bounding box and is defined as

$$IoU = \frac{Area\ of\ Intersection}{Area\ of\ Union}$$

A higher IoU value indicates better localization performance.

Precision measures the proportion of correctly detected objects among all detected objects and is calculated as:

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

where TP represents True Positives and FP represents False Positives.

Recall measures the proportion of actual objects successfully detected by the model and is calculated as:

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

where 'FN' represents 'False Negatives'.

In addition to Precision and Recall, mean Average Precision (mAP) was used as the primary evaluation metric. The mAP@0.5 metric evaluates detection performance at an IoU threshold of 0.5, while mAP@0.5:0.95 provides a more comprehensive assessment across multiple IoU thresholds.

A confusion matrix was also generated to analyze class-wise detection performance and identify possible classification errors between animal classes. These evaluation metrics collectively provide a detailed assessment of the effectiveness of the proposed animal intrusion detection system.

IV. RESULTS & DISCUSSION

The performance of the proposed animal intrusion detection system was evaluated using the test dataset. Standard object detection metrics, including Precision, Recall, mAP@0.5, and mAP@0.5:0.95, were used to assess the effectiveness of the trained YOLOv8n model. Additional analysis was performed using confusion matrices, precision-recall curves, and sample detection outputs.

Training Performance

The YOLOv8n model was trained for a maximum of 200 epochs using the custom animal dataset. During training, both training and validation losses showed a decreasing trend, indicating that the model successfully learned relevant visual features from the dataset.

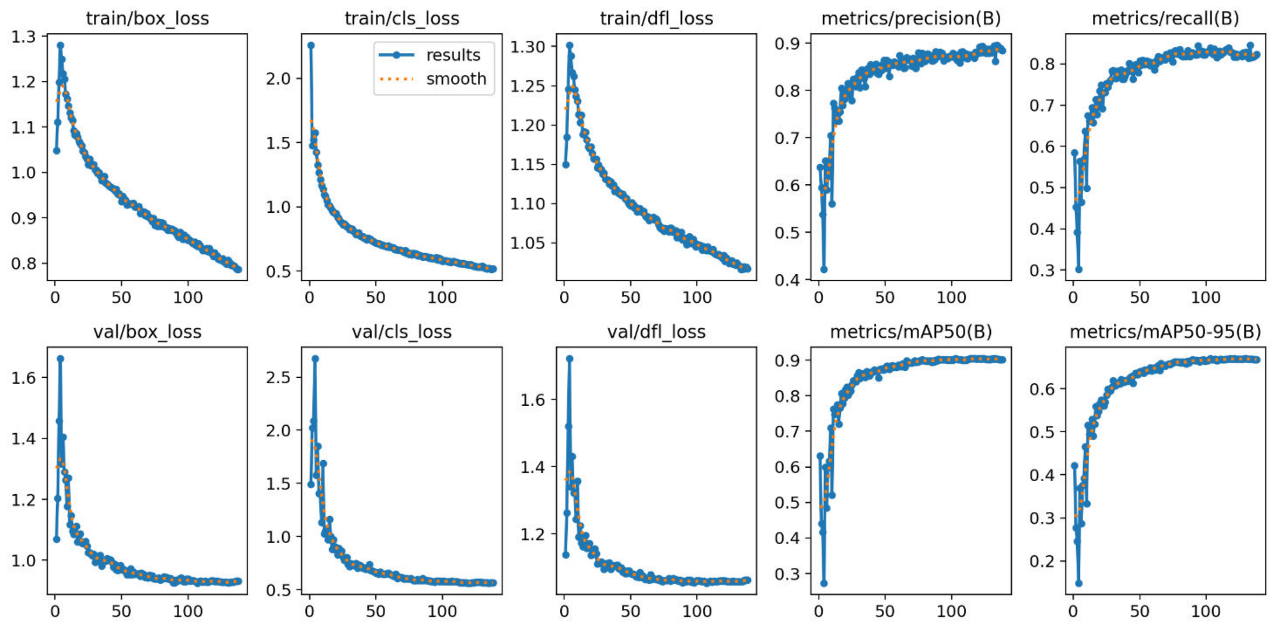

Figure 3

The training curves demonstrate stable convergence without significant fluctuations. Validation performance improved throughout training, suggesting that the model generalized reasonably well to unseen data. The use of data augmentation and validation monitoring helped reduce the possibility of overfitting.

A. Detection Performance

The final model achieved strong detection performance on the test dataset. Table 3 summarizes the overall evaluation metrics.

Table 3

Metric	Value
Precision	88.1%
Recall	83.5%
mAP@0.5	90.59%
mAP@0.5:0.95	66.92%

The obtained mAP@0.5 value of 90.59% indicates that the model was able to accurately localize and classify animals in most test images. The precision value of 88.1% shows that the majority of detections produced by the model were correct, while the recall value of 83.5% indicates that most animal instances present in the images were successfully detected.

B. Class-wise Performance Analysis

To better understand the performance of the model across different animal categories, Average Precision (AP) values were analyzed for each class. The results are presented in Table 4.

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Table 4

Class	AP(%)
Wild Boar	92.0
Elephant	93.4
Cattle	87.8
Buffalo	89.2

The highest detection performance was achieved for the Elephant class with an AP of 93.4%, followed closely by Wild Boar with 92.0%. These results are particularly important because these two classes represent the primary intrusion threats considered in this study.

Cattle and Buffalo achieved slightly lower AP values of 87.8% and 89.2%, respectively. The reduced performance may be attributed to the visual similarity between these two animal classes, which can occasionally result in classification confusion. Despite this challenge, both classes achieved satisfactory detection accuracy.

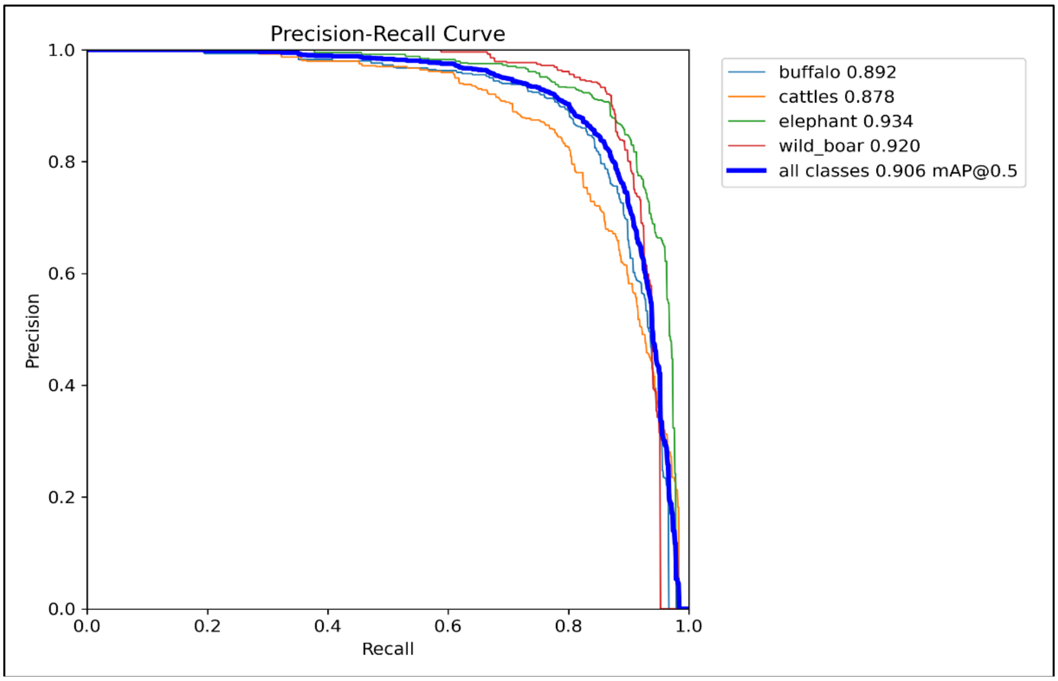

Figure 4

The precision-recall curves further demonstrate the strong detection capability of the trained model across all four classes.

DISCUSSION

The confusion matrix analysis showed that the majority of predictions were correctly classified into their respective animal categories.

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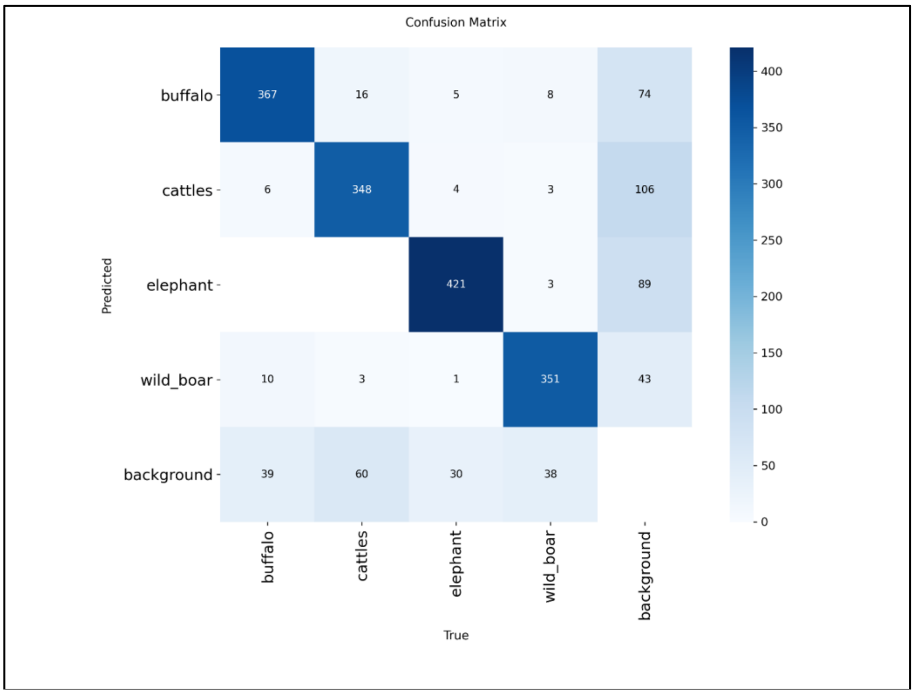

Figure 5

The results indicate that the proposed YOLOv8n-based approach is capable of accurately detecting animals relevant to agricultural monitoring applications. The strong performance achieved for Wild Boar and Elephant detection is particularly encouraging because these animals are commonly associated with crop damage and human-wildlife conflicts.

Sample detection results further demonstrate the ability of the model to correctly identify animals under different viewpoints and background conditions.

Figures 6 & 7

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Although the model achieved strong overall performance, some misclassifications were observed between Cattle and Buffalo classes. This behavior is expected due to the visual similarity between these animals and the variation present within the dataset.

The lower mAP@0.5:0.95 value compared to mAP@0.5 suggests that while the model generally predicts correct object locations, bounding box localization becomes more challenging under stricter IoU thresholds. This is a common characteristic of object detection systems and does not significantly affect the practical usefulness of the model for agricultural monitoring.

Overall, the experimental results demonstrate that YOLOv8n can provide accurate animal detection while maintaining a lightweight model suitable for future agricultural monitoring and intrusion detection applications.

V. CONCLUSION

This paper presented an animal intrusion detection system for agricultural monitoring using the YOLOv8n object detection model. A custom dataset consisting of four animal classes—Wild Boar, Elephant, Cattle, and Buffalo—was collected from publicly available sources, annotated, and used for model training and evaluation. Data preprocessing and augmentation techniques were applied to improve model generalization and detection performance.

Experimental evaluation demonstrated that the proposed model achieved strong detection accuracy, obtaining an overall mAP@0.5 of 90.59% and mAP@0.5:0.95 of 66.92%. The model achieved particularly strong performance for the Wild Boar and Elephant classes, which represent the primary animal intrusion threats considered in this study. The results indicate that YOLOv8n is capable of accurately detecting animals relevant to agricultural monitoring while maintaining a lightweight architecture.

Although the proposed system achieved satisfactory performance, certain limitations remain. The dataset contains fewer samples representing challenging environmental conditions such as heavy rain, fog, and low-visibility scenarios. In addition, some classification confusion was observed between visually similar animal classes such as Cattle and Buffalo.

Future work may focus on expanding the dataset with additional images collected under diverse environmental conditions and incorporating more animal classes relevant to agricultural regions. Further improvements may also include evaluation on real-time video streams and integration with automated alert systems for practical field deployment.

In conclusion, the proposed YOLOv8n-based animal intrusion detection system demonstrates the potential of deep learning techniques for supporting agricultural monitoring and reducing the impact of animal intrusions on farmlands.

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