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IoT Enabled Intelligent Crop Protection System Using Computer Vision

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ABSTRACT

Wildlife entering farmland has become a big problem for farmers, especially in places near forests and natural areas. This leads to serious damage to crops and financial trouble. Traditional ways of keeping animals away, like watching manually, using electric fences, or making noise, are often costly, not very effective, or even dangerous for people and animals. This project introduces a smart crop protection system that uses the Internet of Things and an AI-powered drone. The drone is a flying robot with a camera and an AI model that can recognize animals in real time. When it sees an animal, the drone moves on its own using GPS and set boundaries, and then uses non-harmful methods like lights, sounds, or high-pitched noises to scare the animals away. The system uses edge computing, which allows it to work without a constant internet connection, making it good for rural areas. The drone can fly on its own or be controlled from a phone or computer, which saves time and helps increase farm output. Using affordable hardware, free AI tools, and a flexible design, the system is cost-effective, easy to expand, and kind to the environment. This project shows how smart drone technology can help farming be more sustainable while allowing animals and crops to live together peacefully.

Keywords—IoT, Crop protection, Artificial intelligence, Autonomous Drone, Animal Intrusion Detection, Edge Computing, Non-Lethal Deterrents, Smart Agriculture.

1. INTRODUCTION

One of the most significant sources of livelihood and food security is agriculture. However, in recent years, the intrusion of wild animals into agricultural fields has been on the rise due to deforestation and the expansion of agricultural fields around forests. Wild animals like wild boars, deer, monkeys, and birds often enter agricultural fields in search of food, leading to massive damage to crops and resulting in economic losses for farmers. This problem not only impacts agricultural production but also causes stress for farmers who have to keep a constant check on their fields. Conventional crop protection techniques such as manual guarding, scarecrows, electric fencing, and noise-based deterrents are common but have some drawbacks. Manual guarding is a time-consuming process and is not feasible for large-scale farming, while electric fencing is expensive to install and maintain, and also poses a danger to humans as well as animals. In addition, conventional noise-based deterrents may become less effective as animals become accustomed to the regular patterns. This is where an intelligent, automated, and ethical solution is required. However, recent developments in the Internet of Things and artificial intelligence have made it possible to apply smart agriculture. Artificial intelligence-based computer vision technology has the capability to identify objects in images with a high degree of accuracy, and the Internet of Things has made it possible to monitor and control devices from a distance. When combined with unmanned aerial vehicles, it has become possible to develop a flexible and scalable platform for agricultural surveillance.

This proposed project aims to develop an IoT-based intelligent crop protection system with the help of an autonomous drone that is AI-powered. The proposed system makes use of real-time animal detection with the help of an edge AI model and also uses GPS navigation with geofencing to patrol the boundaries of the farm. Once the animal intrusion is detected, the system makes use of non-lethal deterrents such as lights, alarms, or ultrasonic waves to safely remove the animals from the farm. The proposed system will be able to operate even without the need for constant internet connectivity, which makes it ideal for use in remote areas.

2. LITERATURE SURVEY

A. Related Works and Identified Gap

Wildlife intrusion detection in agricultural fields has been a prominent area of research using various techniques, such as UAV surveillance systems, artificial intelligence, and automatic deterrent systems. UAV surveillance systems are also considered efficient in monitoring agricultural fields because of their coverage area. Temesgen et al. proposed a geofenced drone surveillance system to detect deer intrusion in agricultural fields [1]. However, in this paper, the researchers focused more on drone navigation than intelligence. Edge computing-based intelligent systems have also been proposed in various research studies to prevent crop damage. Ojo and Giordano proposed an embedded animal repelling system using edge computing technology to detect animal intrusion in farmland [2]. However, this system focused more on ground detection than aerial detection. Deep learning techniques have also shown promising results in wildlife intrusion detection systems. Ramya et al. proposed a comparison of various wildlife detection techniques, such as YOLOv3, R-CNN, and Random Forest, in crop protection scenarios [3]. The proposed system showed promising results in terms of faster detection using YOLOv3 compared to other techniques. Similarly, Albanese et al. proposed an efficient deployment of deep learning techniques in agricultural monitoring using edge computing [4]. Several research studies have also been carried out to investigate the application of UAVs for wildlife monitoring through aerial imaging. Andrew et al. reported the application of UAVs for animal identification tasks through cameras mounted on the UAVs [5]. Object detection techniques like YOLO were also reported to achieve good performance for object detection on embedded platforms [6], [7].

Several recent research studies also highlight the effectiveness of the application of UAVs with DNNs for agricultural monitoring tasks [9], [15]. However, most of the research studies on UAVs focus on the application of UAVs for single aspects rather than an integrated system.

Based on the literature review, the following research gaps are identified:

- Limited integration of UAVs' mobility with real-time onboard artificial intelligence detection.
- Reliance on cloud-based processing, which is still limited.
- Limited consideration of non-lethal deterrents.
- Limited consideration of autonomous detection-response systems.
- Limited affordability for small-scale farmers.

These gaps showcase the need for a unified, cost-effective, and autonomous crop protection framework for protection of the crops from being ruined by the wildlife animals that enter the farmland causing loss for the farmers in the agriculture field.

B. Critical Limitations In Prior Studies

Although the previous research works have made a substantial impact to the field of intelligent crop protection, some limitations are still present such as

- Some of the AI-based crop detection techniques are cloud-based, leading to network dependence and processing time [2], [4], [10]. Internet access may not be available in some rural areas.
- Most UAV crop monitoring techniques are mainly used for crop surveillance rather than response [1], [5], [11]. This means that human intervention is required in such cases.
- Some deep learning techniques require more processing power and hence may increase the cost of the system [3], [12].
- The deterrent techniques proposed in the previous research may affect some animals and hence cannot be considered an ethical approach. In some cases, the drone may be limited by battery life [13], [15].
- Thus, the existing systems indicate that the existing solutions are either high-priced, partially automated, unprincipled or are not optimized for the real-world deployment in rural areas.

C. Proposed System and How It Address the Gaps

The proposed crop protection system based on the use of AI technology, along with drones, is expected to mitigate challenges that were noted in the previous research works.

- Integration of UAV and Edge AI: The proposed crop protection system uses an autonomous drone along with real-time animal detection. A lightweight YOLOv8 model is integrated with the Raspberry Pi, which is then attached to the drone. This enables the crop protection system to identify animals directly.
- Offline Operation Using Edge Computing: The image processing, as well as the detection, is done offline. This enables the crop protection system to function offline, which is essential for rural farming environments where internet connectivity is limited.
- Autonomous Detection-to-Response Mechanism: The crop protection system uses an autonomous mechanism to respond once the animal is detected. This enables the crop protection system to respond immediately, thereby enhancing the effectiveness of the crop protection mechanism.
- Safe and Non-Lethal Deterrence: The system incorporates safe deterrents like the use of ultrasonic sound, flashing lights, and the use of a buzzer to scare the animals away. This is done without harming the animals, thereby protecting the crops.
- Cost-Effective and Scalable Architecture: The use of cheap hardware components and free software helps keep the development costs low. Moreover, the design is such that it can be easily expanded to cover more area by modifying the drone's flight area.
- Energy-Efficient Operation:The drone is designed to operate within a geofenced area, thereby ensuring that it uses the least power possible.

Thus, by embedding detection, navigation and non-lethal deterrence into a aligned architecture, the proposed system helps in providing a economically practical ,ethical solution the intelligent crop protection.

3. <u>METHODOLOGY</u>

The proposed system combines UAV-based monitoring, deep learning–based object detection, edge computing, and automated deterrence mechanisms to reduce wildlife intrusion in agricultural areas. The methodology is organized into several stages, including dataset preparation, model training, edge deployment, and autonomous monitoring with deterrence activation. Recent studies have demonstrated that integrating UAV platforms with intelligent detection algorithms can significantly improve wildlife monitoring and crop protection in agricultural environments [1], [5]. Similarly, edge-based AI systems have shown promising results in performing real-time detection tasks without relying on cloud infrastructure [2], [4].The proposed system integrates UAV-based monitoring, deep learning–based animal detection, and automated deterrent mechanisms to protect agricultural fields from wildlife intrusion and its workflow is shown in figure 1.

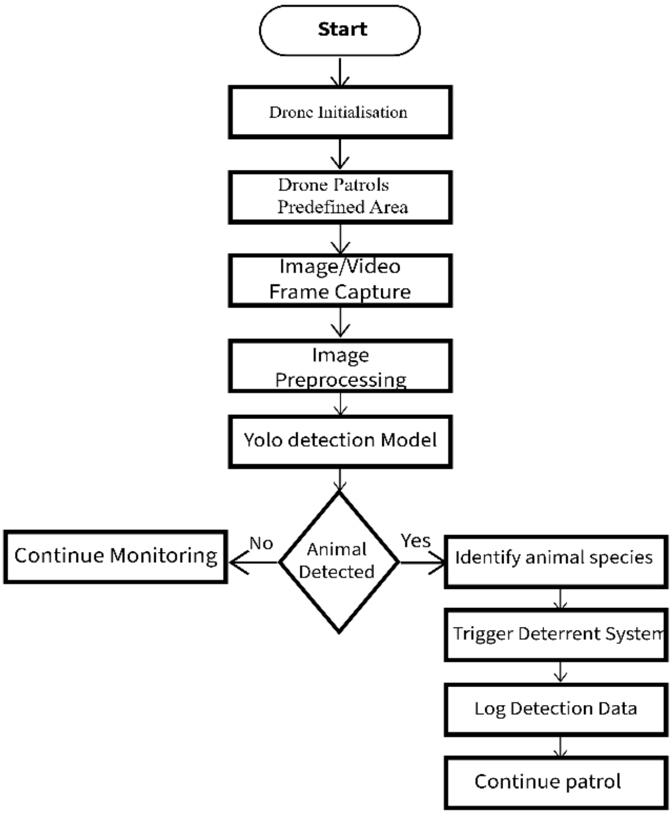

Fig 1 : . Flowchart of Proposed System

A. System Architecture

The architecture of the proposed system has different stages that include collection of data, preprocessing , training the data , and animal detection according to the training. Images are collected using monitoring cameras installed on aerial vehicles like drones where initially, the collected images are categorized into different classes such as tiger, elephant, and wild boar images. After preprocessing the images, they are used to train a convolutional neural network-based animal detection model. After the training process is complete, the model is used to analyse images and detect animals based on features learned during the training process. UAV-based drone systems are often used in environmental and agricultural applications since they can cover large geographical areas efficiently and provide visual information [8], [11]. In addition, geofenced UAVs can automatically patrol specific geographical regions and detect animals that enter the region [1]. With the help of UAVs and deep learning-based animal detection models, the proposed system can effectively provide an animal detection platform.

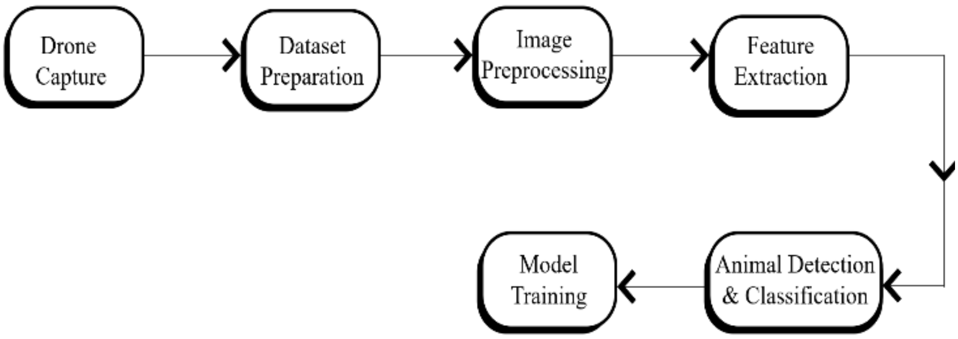

Fig 2 : Flow Diagram of the Proposed Wildlife Detection System

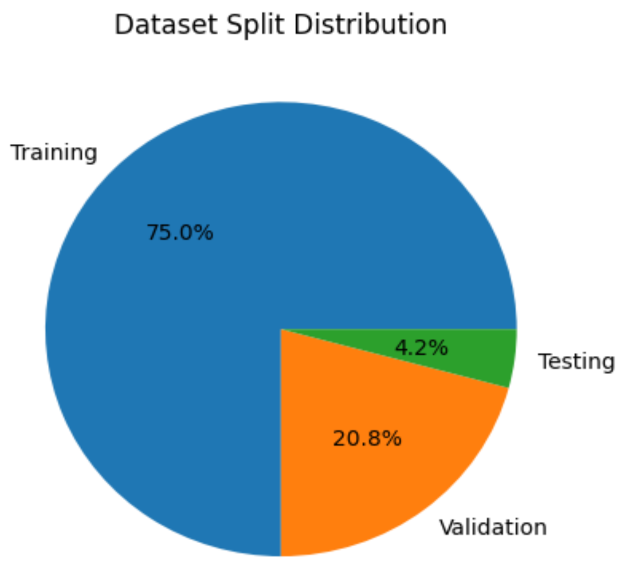

Fig.3 : Dataset split distribution

B. Model Training

A dataset containing wildlife images was obtained from publicly available resources with a focus on including distinct images of the chosen animals. The dataset contains images of the major species of tiger, elephant, and wild boar, which are commonly linked with crop damage in rural areas of agricultural regions. Images were obtained under different environmental conditions like daylight, shadows, occluded views, and distances to make the model more robust when trained with the provided data. Each image was manually labelled according to the animal class to which it belongs. Labelled datasets are considered to be very important when training deep learning models with the aim of performing object detection functions within a complex environment [3], [12]. In addition to that, datasets containing aerial and ground views of wildlife were previously used to train models with the aim of performing detection functions [5], [13].The dataset was divided into several subsets to ensure that the model is trained to learn generalized features rather than focusing on specific examples.

Table 1: Dataset Distribution

Animal Class	Total Images	Training Images	Testing Images	Validation Images
Tiger	1200	900	250	50
Elephant	1200	900	250	50
Wild Boar	1200	900	250	50
Total	**3600**	**2700**	**750**	**150**

C. Image Preprocessing

Prior Before training the model, various preprocessing techniques are carried out to ensure the quality of the data. This will be helpful for the model to learn effectively. The preprocessing stage will involve the following steps:

- Image Resizing: All the images will be resized to a fixed size. For example, the size will be 224 pixels.
- Normalization: The pixel values will be normalized between 0 and 1. This will ensure the stability of the training process.
- Data Augmentation: Data augmentation techniques will be used to increase the diversity of the data. This will ensure that the model can identify the animals regardless of the position from which the image is taken. This technique is widely used in deep learning models to improve the performance of the model [4], [14].

D. Feature Extraction

The system uses deep convolutional neural networks to extract meaningful features from the images of the wildlife species. Convolutional neural networks are very powerful tools for image recognition problems because they are able to automatically learn features from the images. During the feature extraction process, the convolutional layers are able to detect features like edges, textures, and shapes from the images. With the increase in depth, the convolutional neural network starts to learn more complex features like the stripes of the tiger, the body structure of the elephant, and the features of the wild boar.Finally, the pooling layers are applied to reduce the dimensionality of the features extracted from the images. Deep learning-based feature extraction techniques have shown promising results for the detection of the wildlife species [3], [15].

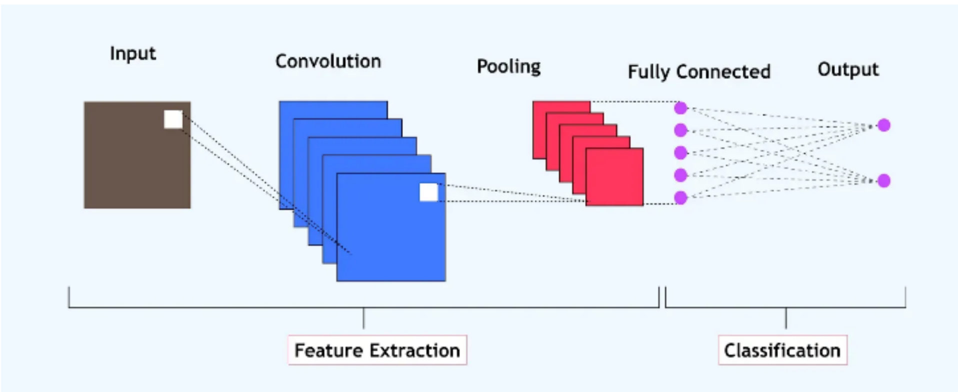

Fig.4 : Convolutional Neural Network Architecture

E. Model Training

The features are then used for training the classification model. As the training progresses, the model learns to map the features to the corresponding animal classes. The training data is split into training and validation sets, which are used to monitor the training progress. This is done to prevent the training model from overfitting the training data.The parameters of the model are optimized using the backpropagation method, which reduces the prediction error during the training epoch.Object detection models, such as YOLO (You Only Look Once), are commonly employed for object detection. YOLO is efficient for real-time object detection, where the object is classified as well as localized. Newer frameworks, such as Ultralytics YOLO, offer efficient tools for training object detection models [7].The performance of the trained model is assessed based on accuracy, precision, recall, and F1-score.

- Accuracy Accuracy measures the overall correctness of the model by comparing the number of correct predictions with the total number of samples. It is defined as

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad 1$$

where TP (True Positive) represents correctly detected animals, TN (True Negative) represents correctly identified non-animal cases, FP (False Positive) represents incorrect detections, and FN (False Negative) represents missed detections.

- Precision measures how many of the predicted positive detections are actually correct. It is calculated as

$$Precision = \frac{TP}{TP+FP} \qquad 2$$

- Recall, measures the ability of the model to correctly detect all actual animal instances in the dataset, expressed as

$$Recall = \frac{TP}{TP+FN} \qquad 3$$

- F1-Score IS the harmonic mean of precision and recall, providing a balanced evaluation of the model's performance given by

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad 4$$

These measures assess the detection and classification ability of the model. Along with the confusion matrix, these measures can be used to assess the ability of the model to correctly classify different animal species and can be used to measure the reliability of the model.

F. Animal Detection and Classification

Once the model is trained, it is deployed to analyze new images and detect animals in real time. In the detection module, images are processed to predict bounding boxes around the detected animals and their respective class labels.If an animal is detected, it is classified into one of the following classes: tiger, elephant, or wild boar.In real-time animal detection systems, early warning systems can be implemented to prevent crop damage and animal attacks [2], [10].The output obtained from the detection module using the YOLO model is shown in Fig. 5.

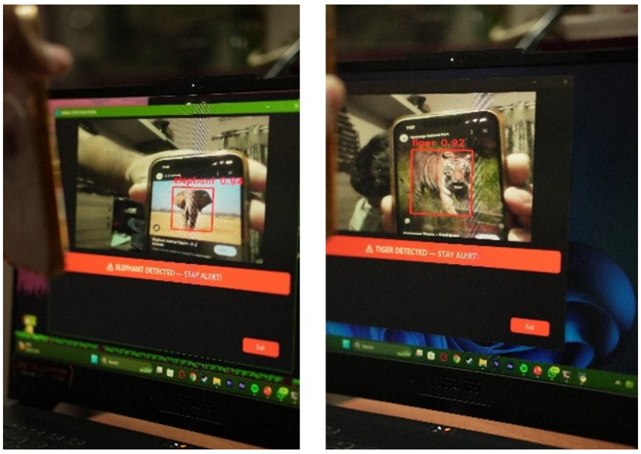

Fig.5 : Animal Detection By YOLO

G. Edge Deployment

The trained model for detection is used for the deployment of a drone-based monitoring system with edge computing. In this system, the edge computing system sends the images captured by the camera mounted on the drone for processing on the computing device.This system reduces the latency period for the detection of animals entering the agricultural area. The images captured by the camera mounted on the drone are processed by the detection model to detect the animals.The usage of AI-based detection systems with UAVs has been effective for the improvement of wildlife monitoring and agricultural protection systems [1], [5], [8], [13].

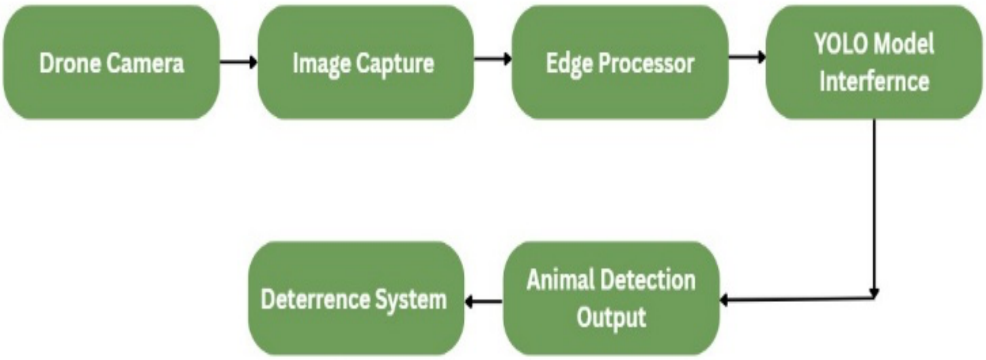

Fig.6 : Edge Deployment Architecture

H. Deterrent Mechanism

The proposed system includes a non-lethal deterrent system that can be used to drive animals away from the agricultural field. Once the animal is detected using the proposed system based on the YOLO model, the controller can be activated to trigger the animal deterrent system, including the use of ultrasonic emitters, buzzer sounds, and flashing lights. This can disturb the animals and encourage them to move away without causing any damage.The proposed animal deterrent system can be connected to the onboard computer using GPIO ports. Once the confidence level is reached with respect to the detected animal, the system can be activated to trigger the animal deterrent system while the proposed system continues to monitor the field.

To enhance the efficiency of the proposed animal deterrence system, different types of sound patterns or frequency can be used to deter different types of animals. For example, low-frequency sound can be used to deter larger animals, while high-frequency ultrasonic sound can be used to deter smaller animals.

4. RESULT AND DISSCUSSION

The proposed wildlife detection system was evaluated using a test data set containing images of tigers, elephants, and wild boars. The trained YOLO-based detection model processed these images and generated a prediction in the form of bounding boxes, class names, and confidence values. YOLO-based object detection models are commonly employed in real-time applications because they perform object localization and classification concurrently, making it suitable for embedded systems [6], [12]. From the experiment, it is clear that the proposed system is capable of detecting the selected species of animals precisely. Detection of elephants was slightly more accurate because of their larger body structure and visual features. However, detection of tigers and wild boars varies slightly because of various environmental factors. Such difficulties in detection have also been faced in wildlife detection systems using deep learning techniques [9], [15].

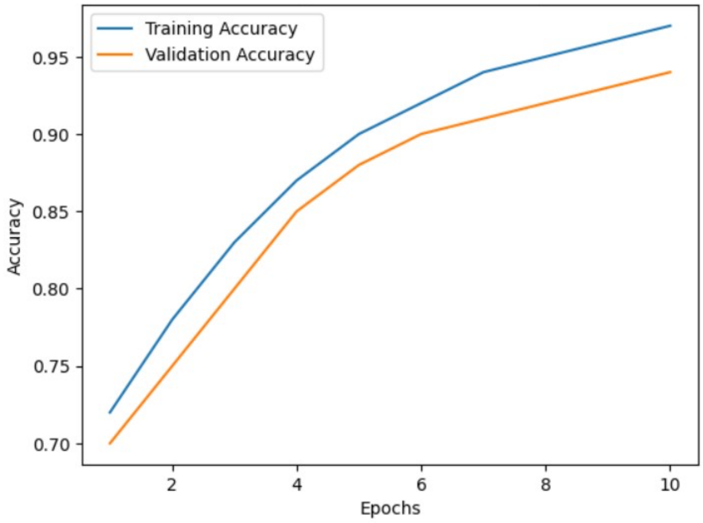

Fig.7 : Training vs Validation Accuracy Curve

The learning behaviour of the model during training is depicted in Fig. 7, where the training accuracy as well as the validation accuracy increases gradually. This indicates that the model is learning the features from the dataset properly. Similar trends of training have been observed for the animal detection systems based on deep learning techniques [3], [12].

Table 2: Performance Metrics

Metric	Value
Accuracy	90.67%
Precision	0.91
Recall	0.91
F1-Score	0.91

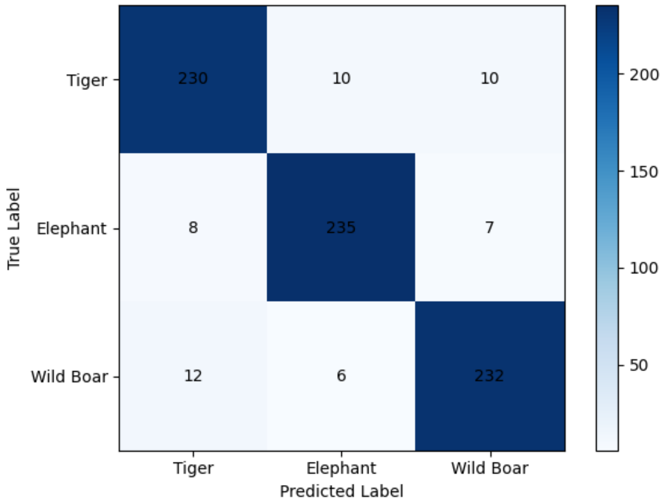

Fig.8: Confusion matrix for animal classification

To In order to assess the performance of the classification, a confusion matrix was created as shown in Fig. 8. It is clear that most of the values are concentrated along the diagonal line, indicating successful classification of the three animal classes.For quantitative evaluation, various performance metrics such as accuracy, precision, recall, and F1-score were employed. It is clear that the system has a high overall detection accuracy of 90.67%, with precision, recall, and F1-score values close to 0.91.Fig. 5 and Fig. 7 show some of the detection images. As shown in Fig. 4, animals are detected and located within a box. It is clear that this system is built on an edge-based drone system, thus enabling real-time monitoring and detection. As shown in various studies, an edge-based AI model improves the efficiency of a UAV system in monitoring wildlife [4], [10], [11], [13].

5. CONCLUSION AND FUTURE SCOPE

This work presented an IoT-enabled intelligent crop protection system that combines UAV-based monitoring, deep learning–based animal detection, and edge computing to reduce wildlife intrusion in agricultural fields. The system utilizes a lightweight YOLO-based detection model deployed on an embedded edge platform, enabling real-time animal detection without relying on cloud connectivity [6], [12]. The experimental results demonstrated reliable detection performance with an overall accuracy of 90.67% for identifying animals such as tiger, elephant, and wild boar.In addition to detection, the proposed system incorporates non-lethal deterrent mechanisms, including ultrasonic sound emitters, LED flash alerts, and buzzer alarms, which are automatically activated when an animal intrusion is detected. These deterrent techniques help repel animals safely while avoiding harm to wildlife and crops. The integration of UAV mobility with intelligent detection and automated deterrence provides an efficient and environmentally friendly crop protection solution [10], [13].

Potential enhancements that could be made to the system include the addition of thermal or infrared cameras to improve the detection capabilities of the system, especially in low-light conditions. There could also be the possibility of coordinating the drones to work in unison to cover larger agricultural areas. There could also be the possibility of incorporating the system with other IoT-based smart farming systems to provide a complete agricultural monitoring system that can be used to manage the farm automatically [9], [15].The proposed system shows the potential that can be achieved through the combined use of AI, UAV technology, edge computing, and automated deterrence in the development of intelligent crop protection solutions. [4], [8].

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