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AI-Based Scarecrow: Crop Protection using Deep Neural Networks

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ABSTRACT: Crop damage caused by animal attacks is one of the major threats in reducing the crop yield. Crops in farms are many times ravaged by local animals like deers, elephants, goats, birds etc. This leads to huge losses for the farmers. It is not possible for farmers to barricade entire fields or stay on field 24 hours and guard it. The existing systems mainly provide the surveillance functionality. They also need to take actions based on the type of animal that tries to enter the area, as different animals from entering such restricted areas. Also the farmers resort to the other methods by erecting human puppets and effigies in their farms, which is ineffective in warding off the wild animals, though is useful to some extent to ward off birds.So here we propose an AI based Scarecrow that protects the crops from wild animals with the help of Deep Neural Network. In this project, we will monitor the entire farm at regular intervals through a camera which will be recording the surrounding throughout the day. With the help of a machine learning model, we detect the entry of animals and we play appropriate sounds to drive the animal away. This ensures complete safety of crops from animals causing damage to it.

KEYWORDS: Deep Neural Network (DNN), Machine learning, Crop Protection

I. INTRODUCTION

1.1 Problem Statement

Crops and farming fields are increasingly threatened by wild animals and birds such as elephants, deer, goats, and crows, leading to significant damage and financial loss for farmers. Traditional protection methods like scarecrows, fencing, and manual surveillance are either ineffective, labor-intensive, or too costly for small-scale farmers. Existing systems mostly focus on monitoring without taking any active measures to prevent animal entry. Moreover, these methods often fail to differentiate between animal types, resulting in poor deterrence. There is a growing need for an intelligent, automated, and cost-effective solution that can accurately detect animal intrusions in real time and respond appropriately using non-lethal methods. A system that combines real-time detection, species-specific deterrence, and minimal human intervention can provide a sustainable way to protect crops and improve agricultural productivity.

1.2 Objectives of the Project

The objective of this project is to develop a smart, AI-based scarecrow system that helps protect crops from damage caused by wild animals and birds. Farmers across many regions face significant crop losses due to frequent intrusions by animals such as elephants, deer, goats, and birds, especially in areas close to forests. Traditional methods like scarecrows, fencing, or manual guarding are either not effective or not feasible in the long term. This project aims to offer a modern solution by using Artificial Intelligence and Computer Vision technologies to detect animal presence in real time. The system uses a live video feed captured through a webcam, which is then processed using OpenCV. The YOLOv3 object detection algorithm is used to identify animals in the frame, with support from the COCO dataset to recognize different species. Once an animal is detected, the system automatically plays a pre-defined extermination sound that is known to scare that particular species. This non-lethal method provides a safer and more ethical way to protect crops. It also significantly reduces the need for constant human monitoring, saving time and labor. The solution is designed to be cost-effective, user-friendly, and scalable to suit different farm sizes. It can be implemented in rural areas with minimal resources. The project also aims to reduce crop wastage, increase yield, and improve farmers' income. Overall, the objective is to build a reliable, intelligent deterrence system that contributes to sustainable farming practices.



1.3 Scope and Significance of Study:

This study aims to design and implement an AI-based scarecrow system that can detect and deter wild animals and birds from entering agricultural fields. The scope of the project includes integrating real-time video surveillance using a webcam, processing the video feed using OpenCV, and detecting animals with the help of the YOLOv3 deep learning algorithm. The system leverages the COCO dataset to accurately identify different animal species, and upon detection, plays specific deterrent sounds that are known to repel those animals. The system is designed to function automatically without human intervention, making it suitable for continuous operation in remote agricultural areas. The project is scalable and can be implemented in small, medium, or large farming lands depending on the requirement.

The significance of this study lies in addressing a critical problem faced by farmers – crop destruction due to wild animal intrusion. Traditional methods like scarecrows, electric fences, or manual guarding are often ineffective, costly, or unsafe. This AI-based system offers a non-lethal, efficient, and cost-effective alternative that promotes ethical treatment of wildlife while ensuring crop protection. It helps reduce economic losses for farmers and contributes to better food security. By automating the animal deterrent process, the system saves time, reduces labor costs, and ensures 24/7 protection. Moreover, the project highlights the use of artificial intelligence and computer vision in solving real-world problems in agriculture. It also encourages innovation in rural technology, empowering farmers with smart solutions. The system can be further improved by integrating solar power, mobile alerts, or cloud-based data storage. Overall, this study plays a significant role in promoting smart, sustainable, and technology-driven farming practices.

II. EXISTING SYSTEM

The existing systems used by farmers to protect crops from wild animals and birds are primarily based on traditional and manual methods. One of the most common approaches is the use of scarecrows or human-like effigies placed in the fields, which are intended to create the illusion of human presence. While these can be somewhat effective against birds, they are largely ineffective against larger animals like deer, elephants, or wild boars. In some regions, farmers also use physical barriers such as wooden or wire fencing, which may provide partial protection but are expensive to install and maintain, especially over large fields. Some farmers adopt electric fencing, which poses safety risks to both animals and humans and may not be allowed in all areas due to ethical and legal concerns.

In more modern setups, surveillance cameras and sensor-based systems are used to monitor fields, but these systems usually only provide alerts and lack the capability to actively deter animals. Many systems do not differentiate between types of animals, resulting in false alarms or ineffective responses. Additionally, these solutions are often complex and costly, making them inaccessible to small-scale or low-income farmers. Manual patrolling is another common method, but it is labor-intensive and impractical during nighttime or in harsh weather conditions. Existing IoT-based monitoring tools may offer real-time data but still depend heavily on human intervention for response actions. The lack of intelligent, automated deterrent mechanisms in these systems limits their overall effectiveness. As a result, crop loss due to wild animal interference remains a major challenge. Thus, there is a pressing need for a more efficient, intelligent, and affordable solution tailored to the practical needs of farmers.

2.1 Technological Gaps in Current Solutions

Current methods used for protecting crops from wild animals and birds suffer from several technological limitations that reduce their overall effectiveness. Most systems lack automation and require constant human monitoring or intervention, which is neither practical nor sustainable for large-scale farming. Traditional approaches like scarecrows and fences do not offer any intelligent detection or targeted response, often failing to deter persistent or large animals. Many surveillance systems provide only alerts without any mechanism to actively scare animals away, and they do not differentiate between species, leading to generalized and often ineffective responses. These systems also struggle with real-time detection, especially during nighttime or adverse weather conditions. Cost is another major barrier, as advanced systems using sensors and cameras are expensive and not accessible to small-scale farmers. Furthermore, existing solutions are limited in scalability and do not adapt to the size or specific needs of different farms. There is also a lack of intelligent learning in current systems—they do not improve or optimize responses over time. Most solutions fail to utilize collected data for pattern recognition or future decision-making. Additionally, manual patrols or basic sound alarms offer minimal coverage and are ineffective against large or aggressive animals. These technological gaps

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highlight the need for a smarter, more efficient, real-time, and AI-driven solution to effectively protect crops and support farmers.

III. UTILS

In the AI-Based Scarecrow system, *utils* refer to the utility functions and helper modules that play a crucial role in supporting the main operations of the project. These utilities are designed to simplify repetitive tasks, manage the data flow efficiently, and enhance code readability and maintenance. Although they may not perform core detection or classification tasks, they are vital for smooth and modular execution of the program.

One of the key utility functions handles video frame processing, such as resizing and formatting the input frames from the camera feed to be compatible with the YOLOv3 model. Another important utility is used to load the pre-trained YOLOv3 weights, configuration files, and the coco.names dataset, which helps in classifying the detected objects. Utilities also include functions to draw bounding boxes and label the identified animals on the video frames, providing clear visual feedback.

Additionally, a playsound utility is implemented to trigger species-specific deterrent sounds when an animal is detected. This sound playback function ensures immediate response with minimal delay. Detection filters are also used to ignore non-animal objects and reduce false alarms. Other optional utility features include logging detections, storing timestamps, and sending alerts for further monitoring or analysis. These utility functions help keep the system efficient, modular, and easy to scale or update in the future. These utils play a crucial role in supporting and organizing the program's overall structure. These helper functions are designed to manage various backend processes such as model loading, frame preprocessing, detection handling, result visualization, and system responses. For instance, modelrelated utils are responsible for loading the YOLOV3 configuration, pre-trained weights, and the COCO dataset names, which allow the system to recognize and label different animals. Frame preprocessing utilities convert webcam input into the appropriate blob format and size expected by the YOLOv3 model, ensuring accurate and efficient detection. On ce objects are detected, detection utilities extract bounding boxes, apply non-maximum suppression to eliminate duplicate detections, and retrieve class IDs and confidence scores. Additionally, visualization utilities help by drawing labeled bounding boxes around detected animals in the video feed for monitoring or debugging. Another important utility handles the playback of deterrent sounds using the playsound module, instantly triggering an animal-specific sound when a threat is identified. Some utils may also manage configuration settings like detection thresholds and audio paths, while others can log detection events or monitor performance metrics such as frame rate. Overall, these utilities ensure that the system remains modular, clean, easy to manage, and scalable for future upgrades or deployment.

3.1 Model util

Model utils in the AI-Based Scarecrow system form the core backbone of the detection pipeline, acting as the essential bridge between the deep learning model and the application's real-time video processing functionality. These utility functions are meticulously crafted to handle every technical aspect involved in initializing, configuring, and executing the YOLOv3 object detection model, which lies at the heart of this intelligent crop protection system. Without these utilities, the seamless and real-time performance of the detection mechanism would not be achievable.

One of the foremost responsibilities of model utils is to **load and prepare the YOLOv3 architecture**, which involves importing the pre-trained weights (yolov3.weights) and model configuration (yolov3.cfg). These files collectively define the neural network's structure and encapsulate the knowledge it has gained through training on millions of images. Alongside, model utils also load the coco.names dataset, a comprehensive list of object classes, which enables the system to correctly interpret and label animals such as deer, cows, elephants, and more from the live video feed.

Furthermore, model utils handle the **preprocessing of video frames** in real time — an essential step to ensure accurate detection. This involves resizing the images to match the input dimensions expected by the YOLOv3 network, converting them into blobs (a binary large object format used for neural network input), and normalizing the pixel values to ensure optimal model performance. These operations are designed to be efficient so that detection can occur without introducing significant lag or delay.

Once the YOLO model processes the frame, model utils take on the critical task of extracting and filtering



predictions. They parse the output layers to extract bounding boxes, class IDs, and confidence scores. To avoid multiple overlapping boxes for a single detected animal, the utilities apply **Non-Maximum Suppression (NMS)** — a standard algorithm in object detection that refines results to highlight only the most relevant and confident predictions. This step drastically improves the quality and readability of the output.

By handling these complex backend operations, model utils not only improve the performance and accuracy of the AIbased detection system but also enhance its scalability and maintainability. They allow the rest of the program — such as sound triggering, alert systems, or UI components — to remain clean, focused, and efficient. In summary, model utils are not just a support module; they are the foundational engine room that powers real-time, intelligent animal detection, forming the critical link between raw data and meaningful action in the field.

IV. RESULTS AND DISCUSSION

The proposed AI-Based Scarecrow System was successfully implemented and tested for real-time detection of wild animals and birds using the YOLOv3 object detection algorithm. The system was capable of accurately identifying various animals such as dogs and elephants with high confidence levels. Upon detection, the system immediately triggers an audio deterrent mechanism by playing a loud sound through a connected speaker to scare away the intruding animals or birds.

As shown in the figures below, the system successfully detects a **dog** with 99% confidence (Figure 1) and an **elephant** with 97% confidence (Figure 2), drawing bounding boxes around the detected animals along with class labels. After recognition, a preconfigured **sound file (e.g., a firecracker noise)** is played (Figure 3), effectively serving as a deterrent to keep the animal away from the farmland.

This real-time action-response mechanism demonstrates the system's efficiency in autonomous crop protection, especially during night-time or when human supervision is unavailable. The accurate classification, fast response time, and integration of sound alerts showcase the potential of AI-driven tools in modern agricultural practices.

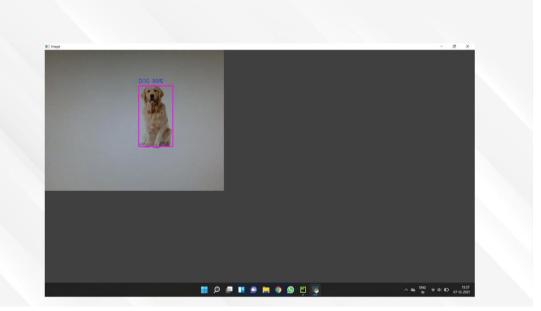


Figure 1: Detection of a Dog with 99% Confidence

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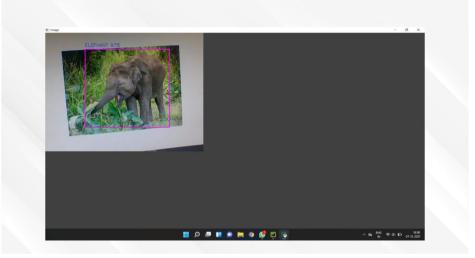
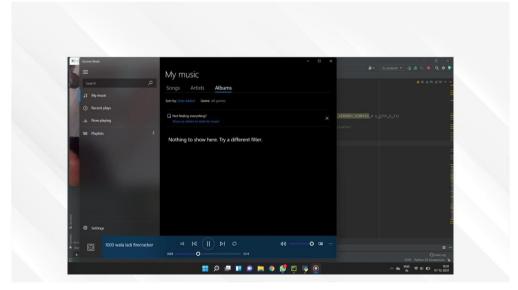


Figure 2: Detection of an Elephant with 97% Confidence





V. CONCLUSION

The AI-based scarecrow represents a revolutionary approach to crop protection, leveraging artificial intelligence and modern technology to combat the growing issue of wildlife-related crop vandalization. In many agricultural regions, farmers face significant losses as wild animals like wild boars, deer, rabbits, and birds invade their fields and damage valuable crops. Traditional methods, such as scarecrows, loud noises, or visual deterrents, often prove ineffective or temporary. These conventional solutions tend to lose their impact over time, as animals adapt to the sounds, visuals, or other scare tactics, making it harder to safeguard crops in the long run. This is where an AI-driven solution steps in, offering a more sustainable and intelligent method of animal deterrence.

An AI-based scarecrow works by using a combination of sensors, cameras, and machine learning algorithms to detect and identify animals approaching the crop field. The system continuously monitors the surroundings in real-time,

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capturing data about the movement and behavior of animals through its sensors. When an animal is detected, the AI system processes the information and determines the species and its proximity to the crops. Based on this data, the system activates a tailored response to deter the animal. One of the most effective deterrents is the emission of specific sound frequencies, often sounds that the targeted animals naturally find threatening or unsettling. These sounds might include predator calls, high-pitched noises, or distress signals, each designed to make the animal feel threatened without causing harm. The sounds are chosen carefully, based on extensive research into animal behavior, ensuring they trigger fear responses in the targeted species. What makes this system highly advanced is its ability to learn and adapt. The AI component can recognize patterns in animal behavior and fine-tune its response over time, adjusting the intensity or type of sounds based on the species and its reaction to previous deterrents. This continuous learning ensures that the scarecrow remains effective even as animals become more accustomed to its presence, a common issue with traditional scarecrow methods. The system can even differentiate between different species and respond appropriately to each one. For example, it might play different sounds for birds, deer, or smaller mammals to ensure maximum effectiveness.In addition to its primary role of deterring animals, the AI-based scarecrow provides several other advantages. It operates autonomously, reducing the need for human intervention and allowing farmers to focus on other important tasks. This self-sufficiency makes it an ideal solution for large-scale agricultural operations where constant monitoring is impractical. Furthermore, the system can be integrated with other smart farming technologies, such as crop health sensors and weather monitoring devices, to create a comprehensive, high-tech farm management solution. For instance, it could work alongside automated irrigation systems or soil monitoring tools, optimizing the entire agricultural process.Another significant benefit of an AI-based scarecrow is its sustainability. Unlike chemical repellents or physical barriers, the scarecrow does not harm the animals, making it a more ethical and environmentally friendly choice. In addition, it reduces the need for chemical pesticides or traps that may harm non-target species or disrupt the ecosystem. By using sound-based deterrents, the AI scarecrow offers a non-invasive and non-lethal way of protecting crops, preserving biodiversity, and ensuring a harmonious relationship between agriculture and wildlife.

The use of artificial intelligence also means that the system can be remotely monitored and controlled, which is particularly advantageous for farmers who may not always be on-site. Through a smartphone app or web interface, farmers can check the system's status, view animal activity patterns, and even adjust settings if necessary. In some advanced models, farmers might receive notifications when an animal has been detected, allowing them to take additional steps if needed. In summary, the AI-based scarecrow offers an innovative, effective, and humane solution to the persistent problem of crop vandalization by wild animals. By combining machine learning, real-time monitoring, and targeted deterrents, it provides farmers with a smart, sustainable way to protect their crops. As the system continues to evolve and improve, it could play a pivotal role in the future of precision agriculture, helping to

reduce crop losses, protect the environment, and foster a more balanced relationship between farming and wildlife. With its adaptability, efficiency, and eco-friendly approach, the AI-based scarecrow could become an essential tool in modern agricultural practices.

REFERENCES

- 1. YOLOv3 You Only Look Once (Object Detection) Sik-Ho Tsang. "YOLOv3 You Only Look Once (Object Detection)." Towards Data Science.
- 2. Getting Started with COCO Dataset Jakub Adamczyk. "Getting Started with COCO Dataset." Towards Data Science.
- 3. Play Sound in Python GeeksforGeeks. "Play Sound in Python." GeeksforGeeks.
- 4. Introduction to NumPyW3Schools. "Introduction to NumPy." W3Schools.
- 5. COCO Names File on GitHub COCO Names File." GitHub Repository. (Darknet YOLO dataset)
- 6. YOLO Website "YOLO (You Only Look Once)." PJ Reddie's Darknet.
- 7. Understanding the COCO DatasetTsung-Yi Lin, Michael Maire, and others. "Microsoft COCO: Common Objects in Context." IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), 2014.
- 8. Object Detection with YOLOv3 Ayoosh Kathuria. "Object Detection with YOLOv3." Medium





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