AI-DRIVEN WILDLIFE DETECTION AND MANAGEMENT SYSTEM FOR AGRICULTURAL PROTECTION

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Abstract—**Environmental harm, safety hazards, and large financial losses are all consequences of human-wildlife conflict, which continues to be a major obstacle to agricultural sustainability. Conventional deterrence techniques, like sound deterrents, personal intervention, and electric fence, have been shown to be ineffective, expensive, and frequently detrimental to wildlife. The AI-driven wildlife identification and deterrence system presented in this study addresses these problems by utilising computer vision, deep learning, IoT-based monitoring, and ultrasound deterrence techniques. Real-time animal detection from live video feeds is achieved by the suggested method using YOLO v11 and OpenCV, precisely identifying species that are a hazard to farmlands. When an animal is detected, an automated ultrasonic deterrence system is triggered, which releases high-frequency sound waves that successfully and safely ward off the animal .In order to help build long-term conservation and conflict mitigation methods, movement monitoring is also integrated to analyse animal migration patterns from reserve forests to places where humans live .Additionally, an Internet of Things-based real-time alert mechanism is included by the system, providing farmers and authorities with immediate notifications by SMS, email, and mobile applications so they may take prompt action. The complete system is made to be economical, environmentally friendly, and scalable, guaranteeing its widespread use in agricultural areas where wildlife intrusions are a problem.**

Keyword—Human-wildlife conflict, agricultural sustainability, AI-driven wildlife detection, deep learning, computer vision, IoT-based monitoring, ultrasound deterrence, YOLO v11, OpenCV, real-time animal detection, automated alert system, movement tracking, conservation strategies, eco-friendly deterrence, non-invasive technology

I. INTODUCTION

Conflict between people and animals is becoming a bigger problem, especially in areas where natural wildlife habitats are bordered by agricultural fields. Deforestation and habitat fragmentation caused by growing human populations force wild animals into farmlands in quest of food, resulting in significant financial losses and endangering both farmers and animals. In addition to destroying crops, these encounters increase hostilities between people and wildlife, which can occasionally result in reprisals that put animal species in even greater risk. To lessen these disputes, conventional deterrent techniques including scarecrow systems, electric fencing, and physical patrolling have been extensively employed. Nevertheless, these methods are expensive, time-consuming, and ineffective in detecting and preventing problems in real time. While manual interventions necessitate constant monitoring and might not be practical in expansive agricultural areas, electric fence can be costly to maintain. Furthermore, some deterrent techniques may harm non-target species and disturb ecosystems, among other negative environmental effects. Rapid developments in computer vision (CV), artificial intelligence (AI), and the internet of things (IoT) have made it possible to repel wildlife in a way that is both sustainable and more effective. Using real-time video feeds, AI-powered wildlife detection systems use deep learning models like YOLO v11 to precisely identify and track animal movements. Instead of using general, one-size-fits-all methods, OpenCV-based image processing algorithms allow for the accurate classification of animal species, enabling targeted deterrence measures.Ultrasound deterrents, a non-invasive technique that uses high-frequency sound waves to repel animals without harming them, are incorporated into the suggested system. The system uses surveillance cameras and motion sensors connected to the Internet of Things to monitor farmlands continuously. When an animal reaches a restricted area, the system instantly activates deterrent devices. Additionally, an automatic alert system minimises crop damage and allows for prompt response times by informing farmers and local authorities by SMS, email, or a mobile application. Real-time Wildlife Detection used to precisely identify wild animals approaching farmlands, use AI-driven object detection.Movement Monitoring and Analysis examine animal migration trends to forecast entry points and support conservation initiatives. Environmentally friendly Ultrasound Deterrence use high-frequency sound waves as a gentle and non-intrusive way to keep wildlife away. Automated Alert System creates a system based on the Internet of Things that notifies farmers and local government representatives instantly. Sustainability and Cost-effectiveness: Create an energy-efficient, scalable technology

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that can be widely used in agricultural environments.This study examines the suggested system's technical design, implementation, and practical effects. The technology promotes a peaceful coexistence between people and animals by improving agricultural security and supporting wildlife conservation initiatives through AI-powered automation. Through the provision of an affordable and sustainable substitute for traditional deterrence techniques, this research seeks to transform agricultural wildlife management and advance a data-driven strategy for mitigating human-wildlife conflicts.

II. RELATED WORK

Using deep learning, the Internet of Things, and real-time monitoring, research on AI-driven wildlife identification and prevention has accelerated significantly. This section examines the body of extant literature, stressing both its strengths and weaknesses.AI-Powered Detection of Wildlife Object detection using YOLO: YOLO (You Only Look Once), a real-time object identification system that is frequently used in wildlife monitoring, was introduced by Redmon et al. (2016)[5]. Additional developments, such YOLO9000 [10] and YOLOv9 [7], increased the precision and effectiveness of detection. YOLO has been used in automatic species identification [8] and camera trap data processing [11]. Models for Deep Learning for a variety of animal species, deep convolutional networks such as ImageNet-based classifiers [4] and gradient-based learning techniques [3] have increased recognition accuracy. Nevertheless, these models frequently call for substantial datasets and considerable processing power. Monitoring of Wildlife Assisted by IoT Smart Sensor Networks: AI and networking are combined in IoT-based surveillance systems, like Watch EDGE [2], to provide real-time environmental monitoring. Ecological camera traps [11] and animal movement analysis [15] have both made use of IoT devices. Nevertheless, active deterrence mechanisms are frequently absent from current methods. Cloud-based AI Processing: While research on cloud-assisted wildlife monitoring [21] shows scalability, real-time processing is made possible by edge computing systems like ultralytics YOLO-NAS [18], which lower latency. Mechanisms for Deterring Wildlife Ultrasonic Deterrence Sharma & Gupta's (2021) research revealed that some species are successfully repelled by ultrasonic sound waves [12]. However, for optimal efficacy, species-specific deterrent frequencies are required [15]. AI-powered Animal Behaviour Analysis: Current models help with adaptive deterrent tactics by detecting and forecasting animal migration [9] [17].AI-Powered Audio-Visual Detection Using OpenCV Audio-Visual Fusion for Animal Detection Norouzzadeh et al. (2018) investigated the application of deep learning models to recognise animals through the use of sound recordings as well as camera-trap images [8].Using OpenCV and YOLO for Sound Analysis numerous AI-driven surveillance systems have investigated the integration of YOLO models with OpenCV-based audio analysis, which allows for the identification of animal cries and their matching with related video frames [5].[10].Analysing Wildlife Behaviour using Sound Detection Species-Specific Deterrence via Ultrasound Identification research has shown that different animal species react differently to ultrasound deterrence [12].

III. PROPOSED WORK

The suggested AI-Driven Wildlife Detection and Management System for Agricultural Protection, designed to identify and control wildlife incursions in agricultural areas, is further explained in this section. For real-time monitoring and deterrent, the system makes use of computer vision, artificial intelligence (AI), and the Internet of Things (IoT). A thorough description of the dataset, methodology, algorithm, and system design that is in line with the project goals can be found below.

A. Dataset

The system needs a customized dataset of photos and videos of agricultural landscapes, including both typical and wildlife intrusion circumstances. The dataset is critical for training the YOLO v11 object detection algorithm to recognize animals in real time.Cameras deployed in agricultural areas provide real-time information on potential wildlife intrusions.Public Wildlife Datasets include iNaturalist, the Wildlife Images Dataset, and other agricultural-specific datasets that include images of common intrusions such as deer, wild boars, and birds. The IoT Sensors used for on-site sensors that provide environmental characteristics such as temperature, sound, and humidity may generate additional data.The size of dataset includes over 10,000 photos and video recordings of numerous animals that are known to trespass on agricultural land, each annotated with bounding boxes. To ensure diversity, this dataset comprises animals in a variety of postures, lighting situations, and times of day.Each image is tagged with the animals bounding box and species identification.Labels are added using YOLO's annotation format, which includes both class IDs and bounding box coordinates (center, width, and height).Image Resizing happens before being fed into the YOLO model, images are scaled to 416x416 pixels.Techniques like as rotation, scaling, flipping, and color modifications are used to expand the diversity of training data by imitating numerous environmental conditions that may effect the field.

B. Methodology

The suggested system's basic methodology combines AI-driven object detection (using YOLO v11), species classification, and IoT-based deterrence. The process is outlined in the steps below:

Wildlife Detection with YOLO v11 is a cutting-edge object identification model that uses photos to identify probable wildlife invasions in real time. The model is trained on the annotated dataset to detect items of interest (such as deer, boar, or birds) in agricultural settings, with high detection accuracy and real-time performance. Following detection, each animal is classified according to the species identified by the YOLO model. This is accomplished by utilizing a CNN classifier that has been fine-tuned to the dataset. The classification guarantees that the system can discriminate between different species, which is critical in deciding the best deterrent approach. When the system detects a species that is considered a hazard (for example, wild boar in a cornfield), it activates an IoT-based deterrence device, such as an ultrasound emitter that sends high-frequency sound waves to repel the animals. Real-time notifications are also given to farm operators, informing them of the identified breach and measures taken. For processing and data storage, the system relies on a cloud infrastructure. The cloud manages incoming data streams from cameras and sensors, while the cloud server performs the heavy lifting of detection and categorization. The cloud also provides real-time notifications via email, SMS, and mobile applications, providing users with up-to-date information about their agricultural security.

C. Algorithm

Video streams of agricultural regions are captured by cameras. New frames are constantly fed into the system for processing. The YOLO input size (416x416) is used to resize the images. To standardize pixel values for quicker model convergence,image normalization is done. Rotation, flipping, and other forms of data augmentation are used during training to enhance generalisation. The YOLO v11 model receives the pre-processed frames as input. YOLO uses bounding boxes and confidence scores to identify possible wildlife when it finds things in the frame. To eliminate unnecessary bounding boxes and guarantee that only the most reliable detection is left, Non-Maximum Suppression (NMS) is used. A CNN-based classifier is applied to the identified objects in order to precisely identify the species. The system decides if a species (like wild boar) is an intruder based on the classification results. When the system detects a confirmed intrusion, the ultrasonic emitter is activated to discourage the wildlife. The farm operator receives a real-time warning from the cloud platform about the identified intrusion and the action that was triggered. The technology continuously scans the farmland and provides real-time detection status updates.

D. System Architecture Diagram

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+-------------------------+
| WILDLIFE DETECTION AI |<---- YOLO V11 MODEL
+-------------------------+
           |
           V
+-------------------------+
|  IOT CAMERA FEED        | ---> IMAGE PROCESSING
(OPENCV)
+-------------------------+
           |
           V
+-------------------------+
| INTRUSION ANALYSIS    | ---> MOTION TRACKING,
SPECIES IDENTIFICATION
+-------------------------+
           |
           V

+-------------------------+                  +----------------+
| ALERT SYSTEM       |---> SMS/EMAIL ALERTS
+-------------------------+                  +----------------+
           |
           V
+-------------------------+
|  DETERRENCE MECHANISM    | ---> ULTRASONIC
EMITTERS, FLASHING LIGHTS
+-------------------------+
           |
           V
+-------------------------+
|  CLOUD & DASHBOARD      | ---> DATA STORAGE,
ANALYTICS, REMOTE MONITORING
+-------------------------+
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IV. RESULT

The AI-Driven Wildlife Detection and Management System was assessed on the basis of deterrence efficacy, species classification, detection accuracy, and system performance. The YOLO v11 object detection model obtained an F1-Score of 92%, a 95% detection accuracy, and 93% precision and 91% recall, respectively. This indicates the system's high capacity to identify wildlife in a variety of agricultural settings. With 92% accuracy, the species classification model—which used a Convolutional Neural Network (CNN)—identified wildlife species, guaranteeing that the proper deterrent measures were implemented.YOLO v11 detected objects in less than 100 milliseconds and finished classifying them in 50 milliseconds, enabling near real-time detection and reaction. The system processed frames in 150 milliseconds.With an 87% success rate, the IoT-based deterrence system was more successful against deer (85%) and wild boars (92%). Within five seconds of identifying an intrusion, the system turned on deterrents.The system effectively deployed deterrents in eight instances over a two-week real-world field test on a 50-acre farm, detecting and responding to ten wildlife invasions. The autonomous functionality of the system and the decreased requirement for manual monitoring were praised by farm operators. The suggested approach provided a more effective wildlife management solution by exhibiting better detection accuracy and real-time response as compared to conventional techniques. In conclusion, the system demonstrated 87% deterrence success, 92% species categorisation accuracy, and 95% detection accuracy, demonstrating its efficacy in safeguarding agricultural regions against wildlife threats.

V. CONCLUSION

In this study, we introduced the AI-Driven Wildlife Detection and Management System for Agricultural Protection, which uses CNN-based species categorisation, IoT-based deterrence mechanisms, and YOLO v11 for wildlife detection. With a 92% species categorisation accuracy and a 95% detection accuracy, the system showed excellent performance. In agricultural settings, the real-time detection and deterrence systems were found to be quite efficient in reducing wildlife intrusions, with an 87% deterrence success rate.The system effectively demonstrated its ability to give timely alerts and automatic deterrence actions in both controlled and real-world agricultural contexts. Our approach dramatically lowers manual labour and improves operating efficiency as compared to conventional techniques.This AI-driven strategy offers a dependable, scalable solution for managing wildlife in agricultural settings because of its high accuracy, fast reaction time, and autonomous capability.Future research will concentrate on strengthening the system's ability to react to changing environmental conditions and refining deterrent tactics, especially for animals like birds. This technology establishes the foundation for combining AI and IoT to solve problems with wildlife management and support sustainable farming methods.

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