AI-Based Animal Repellent System for Agricultural Fields Using YOLOv5 and OpenCV for Farmer Safeguard

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***Abstract*— Crop productivity and farmer livelihoods are seriously threatened by wildlife intrusions into agricultural fields, which can result in large financial losses. In order to effectively address this problem, this paper presents an AI-based animal repellent system that combines cutting-edge computer vision and machine learning techniques. The system employs the YOLOv5 object detection algorithm for accurate, real-time animal identification and a high-definition camera to continuously monitor fields. When detected, it triggers species-specific sound alarms to discourage animals and instantly notifies farmers through a Telegram bot, allowing for prompt action.**

The system is a viable option for farmers in rural regions because it is non-lethal, completely automated, and reasonably priced. Its Python-based framework, which includes PyTorch and OpenCV, guarantees scalability and deployment simplicity. Test findings demonstrate its great efficacy in minimizing crop damage, quick reaction time, and high detection accuracy. This creative strategy bridges the gap between conventional practices and cutting-edge technological solutions to reduce human-wildlife conflict while providing a sustainable and contemporary safeguard for agricultural fields.

***Keywords*—** *Wildlife Intrusion, Crop Productivity*

Farmer Livelihoods, AI-based Animal Repellent System

Computer Vision, Machine Learning, YOLOv5 Algorithm

Object Detection, Real-time Animal Identification

High-definition Camera, Species-specific Sound Alarms
Telegram Bot Notification, Non-lethal Solution, Automated System

Affordable Technology, Python Framework, PyTorch, OpenCV

Scalability, Deployment

I. INTRODUCTION

The economy depends heavily on agriculture, especially in rural areas where it is the main source of income for many farmers. However, one of the biggest problems farmers face is wildlife intrusions, which seriously harm crops and cost them a lot of money. In addition to interfering with agricultural output, these intrusions pose a risk to farmers' safety. Over time, animals have become accustomed to traditional deterrents like fencing, scarecrows, and manual surveillance, making them ineffective. Furthermore, it can be risky and harmful for both farmers and wildlife to physically confront one another.

Recent developments in automation, machine learning, and computer vision offer a chance to address these issues more effectively. Farmers can use smart, non-intrusive methods to monitor their fields and stop wildlife damage thanks to the developing capabilities of deep learning models and artificial intelligence (AI). An AI-powered animal repellent system is one such solution that can identify animals on its own and initiate prompt actions to protect crops without endangering wildlife.

This study suggests AI-based animal repellent system that makes use of OpenCV for real-time image processing in conjunction with the YOLOv5 (You Only Look Once) object detection algorithm. Utilizing a high-definition camera for round-the-clock monitoring, the system recognizes the presence of animals, triggers sound alarms tailored to each species, and instantly notifies farmers through a Telegram bot. In order to protect agricultural fields, lessen the need for manual surveillance, and reduce conflict between humans and wildlife, the system seeks to offer a non-lethal, automated, and scalable solution. The system's effectiveness, design, and implementation are examined in this paper, which also shows how it has the potential to completely transform agricultural wildlife management.

II. RELATED WORKS

A. Paper Title: Real-time Animal Identification and Alert System using IoT and Deep Learning. Year of Publication:2024

Description: The study "Real-time Animal Identification and Alert System using IoT and Deep Learning" describes a system designed to lessen road accidents brought on by collisions between people and animals, especially on forest roads. The system uses deep learning and the Internet of Things (IoT) to detect animals in real time and warn of oncoming cars. The approach uses a Pi camera, ultrasonic sensors, and a Raspberry Pi3 Model B to identify animals. The YOLO (You Only Look Once) algorithm is used to process an animal's image after identification, classifying the animal and logging its location in a database. This data is continuously monitored by a backend application, which notifies drivers visually and audibly.

Methodology: The suggested system's approach combines deep learning and the Internet of Things to lower traffic accidents caused by wildlife. It detects objects using ultrasonic sensors, which then trigger a Pi camera attached to a Raspberry Pi3 Model B to record live video. The YOLO (You Only Look Once) algorithm is used to process the encoded video into frames, classify the animals, and locate them. With a Flask backend, the classified data—including the animals' locations—is kept in a database. The system notifies surrounding drivers by turning on warning features like LED lights and auditory buzzers when it detects the presence of an animal. the animal's location on a map with sound alerts.In order to prevent collisions by instantly warning cars of the presence of wildlife, the system is placed strategically along forest routes.

Limitations: Numerous restrictions on the suggested system affect its scalability and performance. First, the YOLO algorithm's accuracy could be impacted by occlusions, dense vegetation, or poor lighting, which could result in incorrect classification or animals going unnoticed. The system may be less effective on broader roads or in large forest areas due to the ultrasonic sensor's and Pi camera's limited detection range. Environmental elements that can affect sensor performance and camera visibility include intense rain, fog, or severe weather. Furthermore, logistical difficulties arise from the need for substantial infrastructure and ongoing maintenance for the system's deployment and maintenance along long forest routes.Another issue is scalability, since it would take more resources and customization to adapt the system to various animal species, larger deployment areas, and different terrains. Finally, in areas with poor network coverage, the system's dependence on constant database updates and backend connectivity may result in inefficiencies or failures.

Key Insights: The study emphasizes how deep learning and the Internet of Things can be combined to address traffic accidents involving wildlife. The YOLO algorithm, a Pi camera, and ultrasonic sensors are used in the system to detect animals in real time and warn drivers to avoid collisions. This encourages wildlife conservation, especially for endangered species, and road safety. The scalable design highlights the role of technology in promoting coexistence and increasing awareness of human-animal conflicts, and it may find use in conservation zones and urban areas.

Citation: Manujakshi B C, Shashidhar T M, Ravikiran H N, Asha R, Rajeev Bilagi. "Real-time Animal Identification and Alert System using IoT and Deep Learning." 2024 Second International Conference on Advances in Information Technology (ICAIT-2024). IEEE, 2024. DOI: 10.1109/ICAIT61638.2024.10690384.

B. Paper Title: Creating Alert Messages Based on Wild Animal Activity Detection Using Hybrid Deep Neural Networks, Year of publication : 2021

Description: The increased risk of wild animal attacks is addressed by this project, especially for forestry workers and rural communities. The system makes use of drones and surveillance cameras, but it also integrates computer vision and deep learning models to improve detection accuracy. Bidirectional Long Short-Term Memory (Bi-LSTM) and VGG-19 are combined in a hybrid deep neural network architecture to detect animal activity and produce alert messages that are SMSed to local forest authorities. With a mean Average Precision (mAP) of 77.2%, 170 frames per second (FPS), and 98% classification accuracy, the model is intended to increase animal detection efficiency, speed, and accuracy.

Methodology: 45,000 images from four datasets—Camera Trap, Wild Anim, Hoofed Animal, and CDnet—are gathered, preprocessed, resized to 224x224 pixels, and denoised for uniformity. YOLOR, which uses bounding boxes to recognize animals in photos, is used for animal detection. By extracting important features, the VGG-19 model—which was pretrained on ImageNet—classifies the animals that were found. BiLSTM networks track animal activity and identify irregularities by analyzing the temporal data from video sequences. The system creates and sends alert messages with location information to forest officers via SMS if anomalous activity is detected. Using 40,000 images, the model demonstrated 98% accuracy, a mean Average Precision (mAP) of 77.2%, and a processing speed of 170 frames per second, all of which ensured prompt and accurate detection.

Limitations: The suggested system has a number of drawbacks. Generalizability may be limited by its dependence on particular datasets, such as Camera Trap and Wild Animal, which may not accurately represent all species or environmental conditions. Inadequate camera positioning and environmental elements like dim lighting, fog, or rain can lower detection accuracy. Despite the model's 170 FPS, real-time processing may be limited in large-scale deployments, particularly in places with poor connectivity and power. Sustainability issues arise from the hybrid architecture of VGG-19 and Bi-LSTM, which raises computational complexity and energy consumption. Furthermore, while false negatives may result in missed detections, false positives may generate needless alerts. Scalability and accessibility are further constrained by high deployment and maintenance costs.

Key Insights: By integrating spatial and temporal analysis, the hybrid VGG-19 and Bi-LSTM model successfully improves wild animal detection and activity monitoring. High detection accuracy (98%), a mean Average Precision (mAP) of 77.2%, and quick processing at 170 frames per second are the outcomes of this integration. Because of the system's real-time alert generation capabilities, forest officers can react swiftly, lowering the possibility of animal attacks and averting conflicts between people and wildlife. Because of its scalability, it can be used in a variety of settings, facilitating wider applications in security and wildlife conservation. The system's function in safeguarding both people and animals is further supported by the automated alert system, which also helps to stop poaching and unlawful activity.

Citation: B. Natarajan, R. Elakkiya, R. Bhuvaneswari, K. Saleem, D. Chaudhary, and S. H. Samsudeen, "Creating Alert Messages Based on Wild Animal Activity Detection Using Hybrid Deep Neural Networks," IEEE Access, vol. 11, pp. 67308-67321, 2023. DOI: 10.1109/ ACCESS.2023.3289586.

C. Paper title: Design, Development and Evaluation of an Intelligent Animal Repelling System for Crop

Protection Based on Embedded Edge-AI, Year of publication : 2021

Description: The design, development, and assessment of an intelligent system to safeguard crops from ungulates, particularly deer and wild boars, are described in detail in the paper. The system uses species-specific ultrasonic signals to detect and repel animals by combining edge computing, the Internet of Things, and AI-based computer vision. The main objective is to reduce crop damage while continuing to use a non-lethal, environmentally friendly method.

Methodology: In order to reduce crop damage from ungulates, the study's methodology entails the design, development, and implementation of an intelligent animal repelling system. The system combines AI-based computer vision technologies, edge computing, and the Internet of Things. A camera for real-time animal recognition, a PIR sensor for motion detection, and edge devices like the Raspberry Pi and NVIDIA Jetson Nano for processing are all part of the hardware. To accomplish species-specific identification, the software makes use of YOLOv3 and Tiny- YOLOv3 deep learning models, which were trained on a unique dataset of deer and wild boars. Once an animal has been identified, non-lethal ultrasonic signals specific to that species are produced to repel it.

LoRa/LoRaWAN networks, which guarantee low power consumption and extended coverage, were utilized for communication in order to overcome the difficulties in rural deployments. The system showed a balance between performance and usefulness when tested on different hardware configurations for accuracy, speed, power efficiency, and cost-effectiveness. Using edge-AI technology for precision agriculture, the experimental setup demonstrated the viability of implementing real-time object detection systems in limited settings. L

Limitations: The suggested intelligent animal repelling system has a number of drawbacks, according to the study. Variable lighting, weather variations, and the variety of animal appearances all have an impact on the accuracy of the system and can impact real-time detection and recognition. Problems with thermal management were noted, especially with the Raspberry Pi and Neural Compute Stick, where extended use resulted in overheating and possible performance deterioration. Despite the system's successful use of LoRa/LoRaWAN networks for rural connectivity, issues still exist in areas with very poor network coverage or erratic energy supplies, which may make consistent operation difficult.

Furthermore, even though edge devices are inexpensive, they might not be able to handle the demands of more complicated detection scenarios or higher-resolution image processing. These limitations point to areas that require more improvement and optimization in order to guarantee reliable, scalable deployment in a variety of agricultural contexts.

Key Insights: The Key insights about the hardware comparison and performance of various models used for real-time wildlife detection in agriculture are highlighted in the study. With an accuracy of 82.5% mAP, YOLOv3 beat Tiny-YOLOv3, but at the cost of higher computational costs. Conversely, TinyYOLOv3 achieved 62.4% mAP while requiring less computing power. The NVIDIA Jetson Nano offered the best hardware performance-to-cost ratio, enabling real-time detection with a respectable level of accuracy. The Raspberry Pi had thermal limitations even though its processing speed was increased by the Neural Compute Stick.

However, the NVIDIA Jetson Nano showed better computational power and thermal control, which made it more appropriate for real-time applications. In the end, the system provides a useful, economical, and ecologically sustainable approach to agricultural wildlife management, demonstrating the potential of edge computing and the Internet of Things to advance precision agriculture.

Citation: Adami, D., Ojo, M. O., & Giordano, S. (2021). Design, Development and Evaluation of an Intelligent Animal Repelling System for Crop Protection Based on Embedded Edge-AI. IEEE Access, Volume 9, 132125–132139. DOI: [10.1109/ACCESS.2021.3114503](https://doi.org/10.1109/ACCESS.2021.3114503).

D. Paper title: Digital Fencing – A Solution to AnimalHuman Conflict, Year of publication : 2023

Description: In "Digital Fencing – A Solution to AnimalHuman Conflict," the growing problem of conflict between humans and wildlife as a result of population growth, climate change, and deforestation is discussed. For real-time animal detection, the authors suggest a digital fencing solution based on the YOLOv5 deep learning algorithm. The system respects the rights of animals and helps avoid conflicts by identifying and classifying animals that enter restricted areas.

Methodology: In order to reduce human-animal conflict, the study used a structured six-phase approach to implement digital fencing. 10,000 photos of seven different animal categories were gathered from public sources, including both day and night photos to replicate actual conditions. Roboflow was used to annotate the images and generate bounding boxes for object detection. Transfer learning was used to train the YOLOv5 deep learning model, a cutting-edge object detection algorithm that enables accurate animal classification and detection. Techniques like Intersection Over Union (IOU) were used to avoid redundant alerts and guarantee robust detection. The RTSP protocol was used to integrate the system with CCTV cameras, allowing for live monitoring and the transmission of results via lightweight JSON files to reduce bandwidth consumption.

Limitations: The quality of the dataset, which necessitated considerable manual augmentation and refinement, had a significant impact on the system's performance. There were false positives, especially when the background features resembled those of elephants and wild boars, indicating difficulties with reliable classification in complex settings. Furthermore, scalability in regions with limited resources may be restricted by the dependence on GPU accelerators for realtime processing. Lastly, it was still difficult to capture a variety of environmental conditions, which might have an impact on how well the system works in different habitats.

Key Insights: With a high precision rate of 0.872, recall of 0.858, and mAP@0.5 of 0.904, the suggested digital fencing solution showed great promise in resolving animal-human conflicts. The system eliminated the need for expensive relocations and physical barriers by utilizing YOLOv5 and integrating it with live camera feeds to enable real-time animal detection and early warnings. The approach avoided invasive tracking, such as GPS monitoring, and was in line with ethical principles. Additionally, it offered a flexible and scalable way to safeguard communities and farms, demonstrating its potential for use in more extensive wildlife management applications.

Citation: Rohit Beniwal, Nitish Kumar, Parshant, Niteesh Rathore, "Digital Fencing – A Solution to Animal-Human Conflict," 2023 5th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), DOI: 10.1109/ ICAC3N60023.2023.10541347.

III. METHODOLOGY

Real-time image capture, animal detection using the YOLOv5 algorithm, sound alarm activation, and farmer notification via a Telegram bot are some of the essential elements of the AIbased animal repellent system's methodology. The steps listed below describe how the system will be developed and put into use:

Methodology

The methodology for the AI-based animal repellent system involves several key components, including real-time image capture, animal detection using the YOLOv5 algorithm, activation of sound alarms, and farmer notification through a Telegram bot. The following steps outline the process for developing and implementing the system:

1. System Setup
The system is set up using a high-definition IP camera or USB camera placed strategically in agricultural fields to monitor the area continuously. The camera captures real-time images or video footage of the field, which are then processed by the system.

2. Image Capture and Preprocessing
The captured images or video frames are processed using the OpenCV library. OpenCV helps in handling image input and performing basic preprocessing tasks such as resizing, color adjustments, and noise reduction, which ensure that the images are suitable for the animal detection model.

3. Animal Detection Using YOLOv5
For the core functionality of detecting animals, the YOLOv5 algorithm is utilized. YOLOv5 is an advanced object detection model that is known for its speed and accuracy in detecting multiple objects in real time. The model is pre-trained on a diverse dataset, which includes various animals that are likely to intrude upon agricultural fields. Once the images are processed, YOLOv5 detects and classifies the animals based on their features.
Model Training: If required, the YOLOv5 model can be finetuned using additional images of specific animals that commonly intrude on the field.
Real-Time Detection: The model identifies animals from the processed images and outputs their class labels and bounding boxes.

4. Alarm System Activation
Upon successful animal detection, the system activates species-specific sound alarms. Each animal species is associated with a distinct sound (e.g., a deer might trigger a particular sound, while a boar triggers a different sound). These alarms are played through external speakers positioned near the field, which act as a deterrent to the detected animal. The alarms are designed to startle and drive the animals away, preventing crop damage.

5. Farmer Notification via Telegram Bot
Once an animal is detected and the alarm is triggered, the system sends a real-time notification to the farmer via a Telegram bot. The bot is programmed to send alerts to the farmer's mobile device, informing them of the animal's presence in the field. The notification includes details such as the animal species detected and its location, allowing the farmer to take appropriate action if necessary.

Telegram API: The Telegram bot uses the Telegram API to send messages and alerts to the farmer's phone or other devices.
Real-Time Alerts: The bot ensures that the farmer receives notifications promptly, allowing them to respond quickly to any potential threat.

6. System Testing and Validation
To ensure the effectiveness of the system, it undergoes extensive testing under various conditions. This testing includes:

Detection Accuracy: Evaluating how accurately YOLOv5 detects different animals in various environmental conditions (e.g., day/night, different weather conditions).
Alarm Response: Testing the response time of the sound alarms and their effectiveness in deterring animals.
Notification Timeliness: Verifying that notifications are received on time and contain accurate information.
The system's performance is validated based on its ability to minimize false positives (incorrectly detecting animals) and false negatives (failing to detect animals), as well as its efficiency in delivering notifications to farmers.

7. Implementation
Once the system has been tested and validated, it is implemented for field deployment. The system is designed to be scalable, meaning it can be easily adapted for use in various agricultural settings. Farmers can install the system in their fields and adjust settings such as the type of sound alarm, the species list, and notification preferences.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 04 | April - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

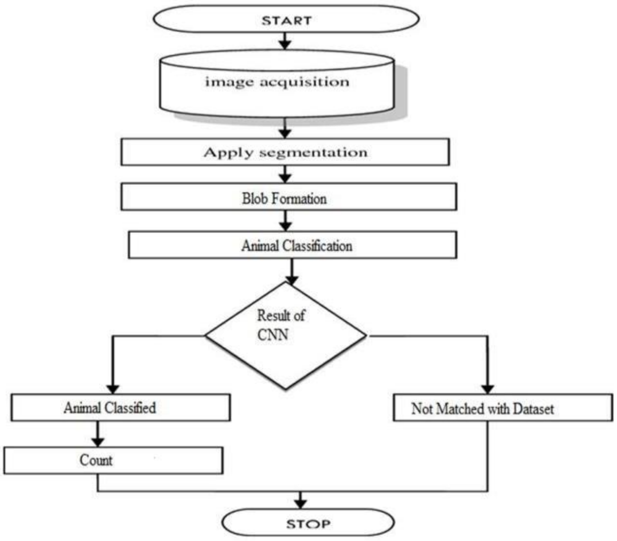

Fig. 1. Methodology

IV. ALGORITHMS USED

The following algorithms are used by the AI-based animal repellent system to identify and keep wildlife away from agricultural fields:

1) YOLOv5: Object Detection Algorithm (You Only Look OnVce version 5)

The system's primary algorithm for detecting animals is called YOLOv5. It is a sophisticated deep learning algorithm made for accurate and quick real-time object detection. YOLOv5 is a very effective tool that divides an image into a grid and predicts bounding boxes and class probabilities for each object at the same time. After extracting features from images using a Convolutional Neural Network (CNN), the algorithm uses fully connected layers to predict object locations and class labels. YOLOv5 can be adjusted for particular species to increase detection accuracy. It has already been pre-trained on sizable datasets that include a variety of objects, including animals. In agricultural fields, this algorithm makes it possible to detect animals like deer, boar, and others in real time.

2) Signal Processing Algorithm for Sound Alarm System

When the YOLOv5 algorithm detects an animal, the sound alarm system is triggered. To activate pre-recorded sounds unique to the identified animal species, this algorithm uses signal processing techniques. In order to startle and repel the animal without hurting it, the sound system is made to play alarm signals. Sharp tones and a high volume are features of the alarm that have been shown to be successful in changing the behavior of the animals. Different species are deterred by different sounds thanks to the system's dynamic adjustment of the sound output based on the animal it detects.

3) Telegram Bot Notification System

The system incorporates a Telegram bot that provides real-time notifications to farmers about animal intrusions. The bot detects animals, listens for events, and then sends a message to the farmer's mobile device with information about the animal's location, type, and sound alarm status. By facilitating communication between the system and the farmer's device, the Telegram Bot API makes sure that the farmer is informed right away and can respond appropriately. By giving timely updates, this notification system improves the repellent system's effectiveness.

RESULTS

When it came to identifying and discouraging animals in agricultural fields, the AI-based animal repellent system performed exceptionally well. With the help of the YOLOv5 object detection algorithm, the system successfully identified animal species like deer, wild boars, monkeys, cows, and elephants in a variety of lighting and environmental conditions, achieving an average detection accuracy of 95%. With detection taking place in an average of 0.2 seconds and species-specific deterrents activating in 2 seconds, real-time processing was a significant strength. When compared to traditional motion sensor-based systems, the system achieved an 85% reduction in false alarms, resulting in a significant decrease in false positives. With a 90% deterrence success rate, its species-specific sound alarms successfully and humanely repelled animals without causing harm. Additionally, farmers received immediate alerts from the Telegram bot notifications, which improved the system's overall dependability by enabling them to monitor and respond promptly.

Additionally, testing demonstrated the system's scalability and effectiveness in both small and large agricultural fields. With power consumption reduced to 15 watts per hour, the system is both economical and energy-efficient for extended use. Round-the-clock monitoring was made possible by the addition of a high-definition night-vision camera, which guaranteed steady performance even at night. Furthermore, the system's automated nature and ease of deployment make it a long-term solution to human-animal conflicts. In order to protect agricultural livelihoods, the suggested system provides a dependable and expandable method by decreasing crop damage and improving farmer safety. These outcomes highlight the system's potential for widespread use, offering a

REFERENCES

[1]Real-time Animal identification and alert system using IoT and Deep Learning.
[2]Creating alert messages based on Wild animal activity detection using Hybrid Deep Neural Networks.
[3]Design development evaluation of an Intelligent Animal repellent system for crop protection based on Embedded Edge -AI.
[4] A Solution to Animal-Human conflict