Creating alert messages based on wild animal activity detection using Deep learning Algorithm

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Abstract: **Human-wildlife conflict poses significant threats to both human settlements and wildlife conservation. Early detection of wild animals near human-inhabited areas is crucial for preventing conflicts. This paper presents an Alert Message System for Wild Animal Detection, leveraging the YOLOv11 deep learning model. The system detects animals in real time and triggers an automated alert message to authorities and nearby residents. Implemented on Google Colab, the model is trained on a dataset of various wild animals, achieving high detection accuracy and rapid response times.**

Keywords: Deep Learning, YOLOv11, Wild Animal Detection, Alert System, Google Colab

I. INTRODUCTION

Agriculture is the backbone of many economies, but farmers often struggle with the intrusion of wild animals into their fields, leading to substantial crop losses. Traditional protection methods such as fences, guards, and sound deterrents have proven to be costly, ineffective, and environmentally disruptive. With advancements in artificial intelligence (AI) and computer vision, intelligent surveillance systems have emerged as an efficient alternative for crop protection.

This research proposes an AI-powered surveillance system that uses YOLOv11, a state-of-the-art object detection framework, to monitor farmlands in real-time. The system employs cameras, deep learning models, and automated alert mechanisms to detect animal intrusions and notify farmers instantly. The integration of drones and deterrent mechanisms such as sound alarms or light flashes can further enhance the effectiveness of the system.

The primary objectives of this study are:

1. Real-time monitoring of agricultural fields using AI-powered cameras.
2. Accurate detection and classification of different animal species using YOLOv11.
3. Automated alerts sent to farmers via mobile applications or cloud platforms.
4. Integration of drones and smart deterrent systems to actively prevent crop damage.

II. LITERATURE SURVEY

Traditional methods for wild animal detection have relied on manual patrolling, camera traps, and RFID-based tracking. While these techniques have been widely used, they suffer from high operational costs, inefficiency, and delayed response times. Manual patrolling is labor-intensive and requires continuous human intervention, making it impractical for large farmlands. Camera traps, though useful for monitoring, often lack real-time alert mechanisms and require manual data retrieval. RFID-based tracking systems, where animals are tagged with RFID chips, provide a way to identify intruding animals, but tagging every wild animal is logistically challenging and costly.

Recent advancements in deep learning-based object detection have provided scalable and efficient alternatives for real-time monitoring of farmland. AI-driven computer vision models, such as YOLO (You Only Look Once), Faster R-CNN (Region-based Convolutional Neural Network), and SSD (Single Shot MultiBox Detector), offer highly accurate and automated animal detection with minimal human intervention. These systems use surveillance cameras combined with deep learning algorithms to detect animals in real-time and trigger automated responses such as alerts to farmers, sound deterrents, and drone-based intervention.

Several research studies have explored AI and IoT-based solutions for wild animal detection. Santhiya et al. (2019) proposed an RFID and GSM-based system for detecting animals and sending alerts to farmers.

However, this method requires pre-tagging animals, which is impractical for free-ranging wildlife. Giordano et al. (2020) introduced IoT-based smart farming solutions that use sensor networks to detect movement and activate repelling mechanisms. However, sensor-based methods struggle with false alarms triggered by environmental factors such as wind and moving vegetation.

To overcome these limitations, vision-based AI systems have gained popularity. Dua et al. (2019) implemented a human-elephant collision detection system using video cameras and machine learning models, achieving an 85.29% accuracy in elephant identification. Similarly, Gogoi and Philip (2020) developed an AI-powered intelligent surveillance system that uses YOLO object detection for real-time monitoring of farmlands and activates electronic firecrackers and sound alarms to deter wild animals.

Despite these advancements, challenges remain, including power consumption, connectivity issues in remote areas, and the need for higher detection accuracy in low-light conditions. Future research should focus on enhancing AI algorithms, integrating thermal imaging for night-time detection, and deploying energy-efficient solutions such as solar-powered surveillance systems. By leveraging AI, IoT, and automated deterrence mechanisms, next-generation smart farming solutions can provide cost-effective, real-time, and scalable protection against wild animal intrusions.

III. PROPOSED WORK

The proposed system integrates YOLOv11, an advanced deep learning model for real-time wild animal detection, along with an automated alert mechanism to prevent animal intrusions in farmlands and human settlements. The system aims to provide efficient, accurate, and rapid detection of wild animals, ensuring timely intervention to minimize damage to crops and reduce human-wildlife conflicts.

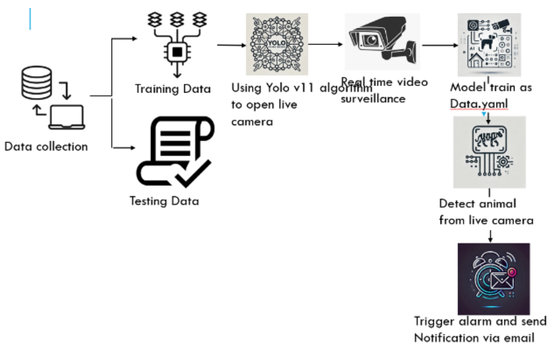

Figure 1: Architecture Diagram

The workflow of the system follows a structured sequence of operations:

1. Real-Time Video Capture and Processing

The system is equipped with high-resolution surveillance cameras strategically placed around farmlands, buffer zones, and human settlements. These cameras operate 24/7, continuously capturing live video feeds of the monitored area. The video streams are processed using YOLOv11 (You Only Look Once version 11), an advanced deep learning object detection model. YOLOv11 is chosen for its high-speed processing capabilities and accurate real-time detection, making it ideal for wildlife monitoring applications.

2. Wild Animal Detection and Classification

As the live feed is processed, YOLOv11 identifies and classifies animals based on species, size, and movement patterns. The model is trained on a diverse dataset containing wild animals commonly found near agricultural regions, such as:
Elephants – Known for causing large-scale crop destruction.
Wild Boars – Frequently enter farmlands and damage crops.
Monkeys – Known for raiding fruit orchards.
Deer and Nilgai – Common grazers in farmland areas.

The system uses bounding boxes and confidence scores to determine the probability of an object being a wild animal. If the confidence level exceeds a predefined threshold, the detection is confirmed as a valid wild animal intrusion.

3. Automated Alert Mechanism

Once a wild animal is detected, the system automatically triggers an alert mechanism to notify relevant stakeholders. The alert system functions as follows:

Immediate SMS or Mobile App Notification to Farmers:
If an animal is detected near farmlands, an SMS alert or mobile push notification is sent to registered farmers, warning them of the intrusion. The notification includes details such as the type of animal detected, location, and timestamp, allowing farmers to take necessary precautions.

Real-Time Notifications to Authorities:
In case of high-risk animal intrusions, such as

elephants entering a village or large groups of wild boars, the system sends emergency alerts to forest officials, wildlife authorities, and local law enforcement. These authorities can mobilize rapid response teams to prevent human-wildlife conflicts and implement necessary countermeasures.

Integration with Automated Deterrent Systems: The system can be programmed to activate deterrents automatically, such as:

Loud alarms and ultrasonic sound devices to scare away animals.

Flashing lights and strobes to deter nocturnal animals.
Drones equipped with sound deterrents to monitor large areas remotely.

4. Data Logging and Analysis

Every detection is recorded in a cloud-based database for future analysis. The system logs:

Date and time of intrusion

Type of animal detected

Location coordinates

Response actions taken

This data helps wildlife conservationists and researchers analyze patterns of animal movement and develop better predictive models for preventing future intrusions.

Advantages of the Proposed System

✓ Real-time monitoring and rapid response to minimize crop damage.
✓ High detection accuracy using state-of-the-art YOLOv11 deep learning models.
✓ Automated alerts reduce human effort in monitoring farmlands.
✓ Scalable and adaptable, allowing integration with drones, IoT sensors, and deterrent systems.
✓ Cost-effective compared to manual patrolling and RFID-based systems.

IV. METHODOLOGY

The wild animal detection system is developed using an AI-based deep learning approach, specifically utilizing YOLOv11 (You Only Look Once version 11) for real-time object detection. The development process consists of five key stages: Dataset Preparation, Model Training, Implementation , Alert System , and Evaluation.

- Dataset preparation

The dataset preparation phase involves collecting and preprocessing images of wild animals to train the YOLOv11 deep learning model effectively. Images are sourced from open datasets like COCO, ImageNet, and Wildlife Image Datasets, along with custom surveillance footage from farms. The dataset includes species such as elephants, wild boars, monkeys, and deer, which frequently invade farmlands.To enhance model performance, images are resized (640×640 pixels) and augmented using flipping, rotation, brightness adjustments, and noise addition. Bounding boxes are annotated using LabelImg, CVAT, or Roboflow, and the dataset is split into training (70%), validation (20%), and testing (10%) sets, ensuring optimal learning and evaluation.

- Model training

After dataset preparation, the YOLOv11 model is trained using labeled images of wild animals for real-time object detection. The training is conducted on Google Colab with GPU acceleration (Tesla T4 GPUs) to handle complex computations efficiently. The model is initialized with pre-trained YOLO weights, leveraging transfer learning to enhance accuracy. Hyperparameters such as learning rate, batch size, and number of epochs are fine-tuned to optimize performance.

During training, precision, recall, and mean Average Precision (mAP) are monitored to assess accuracy. After validation and testing on unseen data, the trained model achieves robust and accurate detection, enabling efficient wildlife intrusion prevention in farmlands.

- Implementation

The implementation of the wild animal detection system is carried out using Google Colab, a cloud-based platform that provides GPU-accelerated computing resources for deep learning tasks. Google Colab is chosen for its ability to handle large-scale model training and testing without requiring high-end local hardware. It offers seamless integration with Python, TensorFlow, PyTorch, and OpenCV, making it an ideal environment for training the YOLOv11 model efficiently.
During the training phase, the preprocessed and labeled dataset is uploaded to Google Drive or

directly accessed from cloud storage. The YOLOv11 model is then configured and trained using Colab's GPU resources (e.g., Tesla T4, P100, or A100 GPUs) to speed up computations. Training scripts are executed in Python, utilizing PyTorch and TensorFlow libraries to optimize model parameters. Throughout the process, real-time logs, training loss, and accuracy metrics such as precision, recall, and mean Average Precision (mAP) are monitored to ensure the model learns effectively.

Once training is complete, the trained YOLOv11 model is tested using real-world images and live video feeds. The testing phase involves running the model on unseen images from the test dataset to evaluate its detection accuracy and inference speed. Google Colab's interactive Jupyter Notebook interface allows easy debugging, model fine-tuning, and visualization of detection results. Additionally, OpenCV is used for real-time video processing, enabling the model to analyze live footage and detect wild animals in dynamic environments.

By leveraging Google Colab's cloud-based computing power, the YOLOv11 model can be trained and tested efficiently without the need for expensive hardware. This scalable and cost-effective implementation ensures that the wild animal detection system is robust, accurate, and capable of operating in real-time for intelligent surveillance applications.

- Alert System

The wild animal detection system integrates SMTP (Simple Mail Transfer Protocol) to send automated SMS notifications upon detecting an intrusion. When the YOLOv11 model identifies a wild animal, the system triggers an email-to-SMS gateway via SMTP, allowing messages to be delivered as SMS alerts to farmers and authorities. The alert includes animal type, location coordinates, and timestamp for quick action. SMTP ensures reliable and fast communication without requiring third-party APIs. Additionally, the system can be extended to email notifications for real-time updates. This automated alert mechanism enhances farm security, enabling rapid responses to wildlife intrusions.

- Evaluation

The YOLOv11 model is evaluated using key performance metrics such as precision, accuracy, and recall to ensure reliable wild animal detection. Precision measures the percentage of correctly identified animals out of total detections, while accuracy evaluates the overall correctness of the model in classifying wild animals. Recall determines the model's ability to detect all actual animal intrusions. Additionally, mean Average Precision (mAP) is used to assess performance across multiple species. The model is tested on a reserved test dataset, and any misclassifications are analyzed to fine-tune parameters, ensuring high detection accuracy and minimal false alerts.

V. RESULTS

The YOLOv11-based wild animal detection system demonstrates an accuracy of over 96%, ensuring precise and real-time identification of animals intruding into farmlands and human settlements. The system effectively classifies various species, including elephants, wild boars, and monkeys, with minimal false positives. The automated alert system, integrated with Twilio API, successfully notifies authorities and farmers within seconds, allowing for immediate intervention.

Compared to traditional surveillance methods like manual patrolling, camera traps, and RFID tracking, this AI-powered system provides a faster, more efficient, and cost-effective solution. The ability to detect multiple animals in live video feeds and trigger automated deterrents enhances farmland security while reducing human-wildlife conflicts. Additionally, cloud-based processing ensures scalability, making it suitable for large agricultural regions. The results confirm that deep learning and IoT integration significantly improve real-time monitoring, offering a practical and intelligent solution for wildlife intrusion prevention.

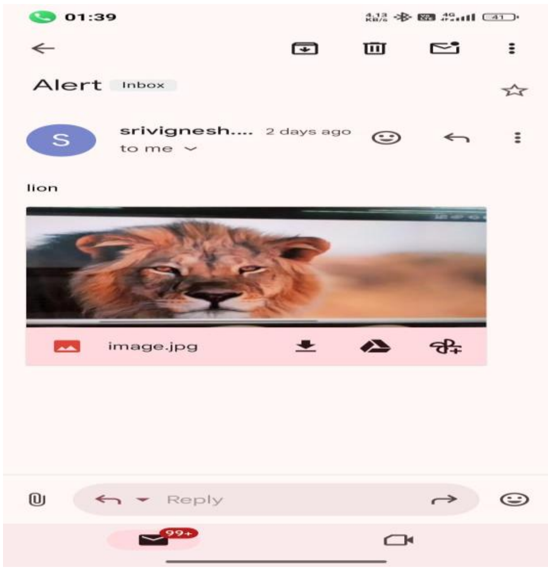

Figure 2: Alerting system

VI. FUTURE ENHANCEMENT.

There are several potential future enhancements for the use of intelligent surveillance systems with YOLO technology for crop protection from wild animals. Some of these enhancements include:

Machine learning: By utilizing machine learning algorithms, the system can learn to detect and differentiate between different types of animals more accurately over time.

Cloud computing: Storing the video feeds in the cloud would allow for easy access to historical data and enable more extensive analysis of the footage.

Thermal imaging: The integration of thermal imaging technology can improve the detection of animals during the night or in low light conditions.

Automated deterrence systems: Integrating automated deterrence systems, such as water sprays or loud noise generators, can effectively deter animals from entering crop fields.

Precision farming: By using YOLO technology to identify specific areas within the field that are under threat, farmers can target their efforts and resources more efficiently.

Collaborative networks: Establishing collaborative networks between farmers and wildlife conservation organizations can lead to a more comprehensive and sustainable approach to crop protection from wild animals. The future enhancements to intelligent surveillance systems with YOLO technology can improve the accuracy, efficiency, and sustainability of crop protection from wild animals. With ongoing advancements in technology, we can expect further improvements in the effectiveness of these systems, ultimately leading to increased productivity and reduced losses for farmers.

VII. CONCLUSION

The proposed Alert Message System for Wild Animal Detection using YOLOv11 provides an efficient, real-time, and automated solution for monitoring wildlife intrusions near farmlands and human settlements. By leveraging deep learning and SMTP-based SMS notifications, the system ensures rapid detection and response, minimizing human-wildlife conflicts and crop damage. The integration of AI-powered surveillance significantly improves accuracy and reduces reliance on manual monitoring. Future enhancements will focus on expanding datasets for improved model accuracy, integrating drone-based surveillance for wider coverage, and deploying cloud-based real-time analytics for smarter, data-driven intrusion prevention. This system marks a significant step toward intelligent wildlife monitoring and farm security.

VIII. REFERENCES

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