Wild Animal Detection and Alerting System

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Abstract— Human–wildlife conflict is a major challenge in areas where agricultural fields and human settlements border forests, often resulting in crop damage, property loss, and safety risks. Traditional preventive measures such as fencing, firecrackers, and manual patrolling are labor-intensive and unreliable. This study proposes a Wild Animal Detection and Alerting System that utilizes the YOLOv8 deep learning model integrated with Python and OpenCV for accurate real-time detection of wild animals. A Streamlit-based interface provides users with interactive dashboards for uploading images or videos, while an SQLite database stores detection records including species, timestamp, and confidence level. To ensure timely response, the system triggers both audio alarms and automated email notifications upon detection. Experimental evaluation demonstrated that the system achieves high accuracy in detecting multiple species, performs efficiently on GPU-enabled systems, and remains functional on CPU environments with slightly reduced speed. The results confirm that the system is effective in reducing human–animal conflicts by providing early alerts, supporting farmers and forest officials, and contributing to wildlife conservation. This makes the solution scalable, cost-effective, and adaptable for large-scale deployment in real-world environments.

Keywords— Wildlife Monitoring, Object Detection, YOLOv8, Real-Time Alerts, Deep Learning, Computer Vision

I.INTRODUCTION

Human–wildlife conflict is a major challenge in regions where agricultural lands are located near forests. Wild animals such as elephants, tigers, and wild boars often intrude into farms and villages in search of food, causing crop losses, property damage, and threats to human safety. Traditional preventive measures such as fencing, firecrackers, and patrolling are labor-intensive and unreliable, highlighting the need for smarter solutions.Recent technological efforts include the use of camera traps, motion sensors, and infrared detectors to monitor wildlife activity. While useful for research, these systems face limitations such as false alarms, inability to classify species, and lack of real-time alerting. As a result, they are not sufficient for proactive conflict management.

Advancements in artificial intelligence and computer vision have opened new opportunities for automated monitoring. Object detection models such as Faster R-CNN and YOLO have achieved high accuracy in identifying animals from images and videos. The YOLOv8 algorithm in particular offers real-time performance with improved accuracy, making it suitable for field applications.

This study presents a Wild Animal Detection and Alerting System that combines YOLOv8 with automated alerts and visualizations, providing a cost-effective and scalable approach to reduce human–animal conflict.

II.LITERATURE SURVEY

Human–wildlife conflict has been managed for decades using traditional methods such as fences, firecrackers, and night patrolling. While inexpensive, these methods are labor-intensive and unreliable, especially in remote areas. To improve monitoring, researchers introduced camera traps, which have been valuable in ecological studies for recording species diversity and animal behavior. However, camera traps lack automation and do not provide real-time alerts.Sensor-based systems, including infrared and motion detectors, have also been tested for animal detection. Although cost-effective, they often produce false alarms due to environmental factors like wind or rainfall and are unable to differentiate between humans, livestock, and wild animals.

The introduction of machine learning improved classification to some extent, but handcrafted features such as HOG and Haar cascades struggled with complex backgrounds and low-light conditions. Recent advances in deep learning and object detection, particularly the YOLO family of algorithms, have transformed wildlife monitoring by enabling real-time detection with high accuracy. Among these, YOLOv8 offers improved speed and precision, making it suitable for field deployment.

III.METHODOLOGY

The proposed system employs a deep learning–based approach for detecting wild animals in real time and generating automated alerts. The methodology integrates object detection, alert generation, and data visualization to ensure accurate monitoring and practical usability.

First, data collection and preprocessing were carried out using open-source datasets containing images of multiple animal species. Images were resized, normalized, and annotated to prepare them for model training.

Next, the YOLOv8 model was adopted due to its high speed and accuracy. The model was trained and tested using Python and OpenCV, ensuring robust detection even under varying lighting and environmental conditions.

The detection module was connected to an alerting mechanism, which triggers audio alarms and sends email notifications immediately after an animal is identified. This minimizes response time and improves field applicability.

Finally, a Streamlit dashboard was developed to provide a user-friendly interface. The dashboard displays detection results, statistical visualizations, and a location map for geo-tagged events, while also allowing export of detection logs.

This integrated methodology enables a cost-effective, scalable solution for real-time wildlife monitoring and conflict prevention.

IV.SYSTEM DESIGN

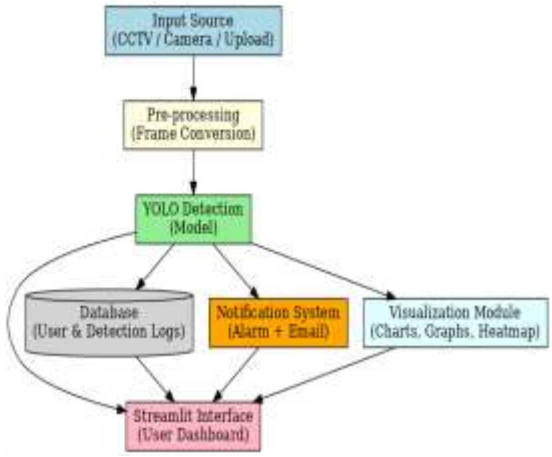

Figure 1: System Architecture.

V. RESULTS ANDOUTCOMES

The implementation of the Wild Animal Detection and Alerting System demonstrated reliable performance across various test scenarios. Using the YOLOv8 model integrated with Python and OpenCV, the system successfully detected multiple species in real-time video streams with high accuracy. On GPU-enabled systems, the detection speed averaged 30–40 frames per second, making it suitable for live monitoring.

The alerting mechanism, which included both email notifications and an audio alarm, functioned without delays, ensuring immediate response when an animal was detected. Streamlit provided an interactive dashboard where users could view

Testing also confirmed the system's robustness under varying lighting conditions and complex backgrounds. False positives were minimized through efficient preprocessing and optimized confidence thresholds.

Overall, the results validate that the proposed system can effectively reduce human effort, improve safety in farmlands and forest boundaries, and support conservation practices through accurate, real-time animal monitoring and alerting.

Figure 2: Detect The Animal And Send Mail Notification

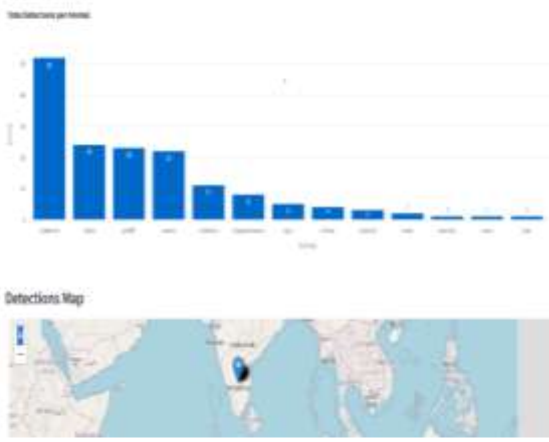

Figure 3: Detection Dashboard

VI.CONCLUSION

The proposed Wild Animal Detection and Alerting System demonstrates how deep learning and computer vision can effectively address the problem of human–wildlife conflict. By integrating the YOLOv8 model with Python and OpenCV, the system is capable of detecting multiple animal species with high accuracy in real time. The addition of an automated alert mechanism, consisting of audio alarms and email notifications, ensures timely response to potential threats. Furthermore, the use of an SQLite database and Streamlit-based interface provides structured data storage and meaningful visualization of intrusion patterns.

The evaluation of the system confirms its practical utility, as it performed reliably across diverse inputs and environmental conditions. Unlike traditional methods or sensor-based systems, this approach offers both automation and scalability while remaining cost-effective. Overall, the research contributes to wildlife protection efforts by providing a solution that reduces risks for farmers and forest officials while supporting data-driven conservation practices.

VII.REFERENCES

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