Real-Time Hazardous Animal Detection for Agricultural Fields and Forest Areas Using Deep Learning

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Abstract

Human–animal conflict in agricultural and forest-border regions has become a major concern, causing crop damage, economic losses, and safety risks. This paper presents a real-time hazardous animal detection system using deep learning to address these challenges. The proposed system utilizes the YOLO (You Only Look Once) object detection model to detect animals from live video streams. The model is trained on a diverse dataset to ensure reliable performance under different environmental conditions. Detected animals are further classified into hazardous and non-hazardous categories, where dangerous animals trigger visual and audio alerts for immediate response. The system is currently implemented using a browser-based camera interface for real-time testing and accessibility. In future deployment, the system can be integrated with CCTV infrastructure and edge devices for continuous monitoring in remote areas. The proposed approach provides a scalable, cost-effective, and intelligent solution to reduce human–animal conflict and improve safety in agricultural and forest environments.

Keywords- Deep Learning, YOLO, Hazardous Animal Detection, Computer Vision, Human–Animal Conflict, Smart Agriculture

1. Introduction

Human–animal conflict has become a significant challenge in agricultural and forest-border regions, leading to crop damage, economic loss, and risks to human life. Increasing human encroachment into wildlife habitats has resulted in frequent intrusion of animals such as elephants, wild boars, and leopards into farmlands. Traditional monitoring methods rely on manual surveillance, which is inefficient and incapable of providing timely alerts.

Recent advancements in artificial intelligence (AI) have enabled automated monitoring systems in agriculture. AI-based techniques are widely used for crop monitoring, disease detection, and surveillance, improving efficiency and reducing manual effort [1]. Deep learning models such as YOLO and Faster R-CNN have demonstrated strong performance in real-time object detection tasks, making them suitable for detecting hazardous animals in surveillance systems [2], [3].

Several studies have explored the integration of AI with IoT and sensing technologies to enhance smart agriculture systems. These systems enable real-time monitoring and early detection of threats, allowing farmers to take preventive action [4]. Additionally, advancements in drone-based monitoring and sensor technologies have further improved large-scale surveillance capabilities in agricultural environments [5].

Despite these developments, existing systems often face limitations such as high computational cost, lack of real-time alert mechanisms, and reduced performance in complex environmental conditions. Many systems are also not easily scalable for deployment in remote agricultural or forest areas.

To address these challenges, this paper proposes a deep learning-based hazardous animal detection system using YOLO. The system detects animals from video frames and classifies them into hazardous and non-hazardous categories, generating alerts when necessary. The system is currently tested using browser-based camera input and can be extended to CCTV and edge-based deployment for real-time monitoring.

2. Related Work

Several researchers have explored the application of artificial intelligence and deep learning in agriculture and wildlife monitoring. The use of AI in agriculture for automating tasks such as crop monitoring and surveillance has been widely studied, improving efficiency and reducing manual intervention [1]. Similarly, deep learning models such as Faster R-CNN have been used for detecting dangerous animals through real-time video streams, enabling rapid response and reducing losses [2].

YOLO and Faster R-CNN models have been extensively compared, highlighting their effectiveness in object detection applications, including hazardous animal detection in agricultural environments [3]. Furthermore, Faster R-CNN has demonstrated high accuracy in detecting moving objects, making it suitable for real-time surveillance systems [4].

Recent advancements have also focused on integrating AI with IoT for enhanced monitoring, enabling real-time decision-making in precision agriculture [5]. In addition, sensing and computational technologies have been used for monitoring animal behavior and ensuring timely alerts [6].

Modern approaches such as WilDect-YOLO and YOLO-SAG have improved detection accuracy and robustness in complex environments by optimizing YOLO-based architectures [7], [8]. Drone-based monitoring systems have also been explored to enhance large-scale surveillance and early detection of animal intrusion [9].

Although these approaches show promising results, challenges such as real-time deployment, scalability, and environmental variability still exist. These limitations highlight the need for an efficient and scalable hazardous animal detection system, which is addressed in this work.

3. Methodology

The proposed system follows a multi-stage pipeline that integrates deep learning, computer vision, and alert mechanisms to detect hazardous animals in agricultural and forest areas. Initially, the dataset is collected from publicly available sources such as Roboflow wildlife datasets along with additional images extracted from real-world video frames. The dataset includes various animal classes such as elephants, wild boars, leopards, and other animals. All images are annotated using bounding boxes and labelled accordingly. Pre-processing techniques such as resizing, normalization, and data augmentation methods including flipping, rotation, and brightness adjustment are applied to improve model performance under different environmental conditions.

The YOLO (You Only Look Once) model is selected for this system due to its high speed and accuracy in object detection tasks. The model is trained using transfer learning on the prepared dataset, where hyper parameters such as learning rate, batch size, and number of epochs are optimized to achieve better performance. During inference, the trained model processes input frames and generates bounding boxes, class labels, and confidence scores for detected animals. These detected animals are further classified into hazardous and non-hazardous categories based on predefined criteria, where animals such as elephants, wild boars, lions, and leopards are considered hazardous.

The system utilizes a browser-based camera interface to capture frames, which are then sent to the backend server for processing. This frame-based approach enables near real-time detection while ensuring compatibility across devices without hardware dependency issues. When a hazardous animal is detected with sufficient confidence, the system triggers alerts in the form of visual warnings and audio notifications to ensure immediate response. Additionally, detected frames are stored for future analysis and monitoring.

The overall system integrates a frontend interface, backend processing using a Flask server, and the YOLO deep learning model to enable efficient detection and alert generation. Although the current implementation is based on browser-based input, the system is designed to be scalable and can be extended to real-time deployment using CCTV cameras and edge devices such as Raspberry Pi for continuous monitoring in remote areas.

4. Results and Discussion

The proposed hazardous animal detection system was implemented using the YOLO deep learning model and evaluated on a test dataset containing multiple animal classes. The trained model successfully detected and localized animals within input images by generating bounding boxes along with class labels and confidence scores. The system further classified detected animals into hazardous and non-hazardous categories based on predefined rules. Hazardous animals such as wild boars were highlighted using red bounding boxes with warning labels, as shown in Figure 1, while non-hazardous animals such as cows were marked using green bounding boxes, as illustrated in Figure 2. These visual results demonstrate that the model is capable of accurately distinguishing between dangerous and non-dangerous animals under different environmental conditions.

Figure 1: Hazardous Animal Detection using YOLO (Pig – Red Bounding Box)

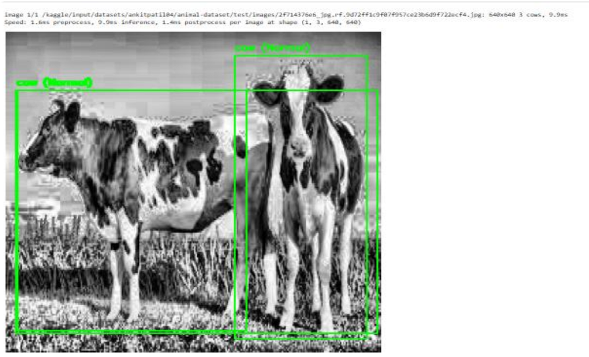

Figure 2: Non-Hazardous Animal Detection using YOLO (Cow – Green Bounding Box)

The performance of the model was evaluated using standard object detection metrics, including precision, recall, and mean Average Precision (mAP). The model achieved a mAP@0.5 of approximately 73%, with a precision of around 80% and recall of about 65%. These results indicate that the model performs reliably in identifying animals with high confidence. However, some limitations were observed, such as occasional missed detections and reduced accuracy in cases involving overlapping animals, complex backgrounds, or low-quality images. Despite these challenges, the model maintains consistent detection performance across most test cases.

The experimental setup primarily focused on backend model training and testing using static images and frame-based inputs. The results confirm that the classification logic for hazardous and non-hazardous animals works effectively, and the bounding box predictions are visually accurate, as evidenced in Figure 1 and Figure 2. The system demonstrates strong potential for real-world application in monitoring animal intrusion in agricultural environments.

In addition to the implemented backend system, a complete real-time detection framework is proposed. This includes integration with a frontend interface, live camera input, and an alert mechanism capable of generating visual warnings and audio notifications when hazardous animals are detected. The current browser-based implementation simulates near real-time detection by processing frames periodically. The proposed system can be further extended to continuous real-time monitoring using CCTV cameras and edge computing devices such as Raspberry Pi, enabling deployment in remote agricultural and forest areas.

Overall, the results demonstrate that the proposed system provides an effective and scalable solution for hazardous animal detection. The combination of deep learning-based detection and rule-based classification ensures reliable performance, while the proposed real-time extension enhances its practical applicability in reducing human–animal conflict and improving safety.

5. Conclusion

This paper presented a deep learning-based hazardous animal detection system aimed at reducing human–animal conflict in agricultural and forest-border regions. The proposed system utilizes the YOLO object detection model to accurately detect animals and classify them into hazardous and non-hazardous categories. The experimental results demonstrate that the model achieves reliable detection performance, with satisfactory precision and mean Average Precision (mAP) values. The system was successfully tested using image-based and browser-captured frames, validating its effectiveness in identifying dangerous animals and generating appropriate visual outputs. Although the current implementation focuses on backend model development and frame-based detection, the proposed system is designed to support real-time deployment with frontend integration and alert mechanisms. In future, the system can be extended to continuous monitoring using CCTV cameras and edge devices, enabling practical deployment in remote agricultural and forest environments. Overall, the proposed approach provides a scalable, cost-effective, and intelligent solution for improving safety and minimizing crop damage caused by wildlife intrusion.

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