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Yolov8 Based Animal Intrusion Detection for Crops Protection

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Abstract: Wildlife intrusion puts limited regions and agricultural fields at risk, resulting in property destruction and crop damage. In order to overcome this difficulty, a sophisticated System uses deep learning to provide protection and monitoring in real time. The system uses the cutting-edge object identification model YOLOv8 to precisely recognize and categorize animals from real time video feeds using OpenCV. It effectively separates animals from people and other objects by using Convolutional Neural Networks (CNNs), guaranteeing accurate detection. In order to help farm owners make better decisions, each discovered animal is labelled with its matching name and confidence score. The technology automatically sends out email notifications when it detects an animal intrusion, lowering manual surveillance efforts and increasing operational efficiency while enhancing security and facilitating quick response. Because of its flexible and adjustable design, it is a dependable way to protect confined areas and agricultural grounds

I. INTRODUCTION

Wildlife intrusions pose significant threats to agricultural lands and restricted areas, causing severe crop damage, financial losses, and property destruction. Traditional monitoring methods relying on human intervention are inefficient, time-consuming, and often fail to prevent damages in real-time. Recent research in deep learning and computer vision have led to the enhancement of automated surveillance systems that improve detection accuracy and responsiveness. Previous studies have introduced AI-based solutions for animal detection, including Deep-AID [1], which enhances precision using hybrid neural networks, and AI-driven road safety frameworks [2] that utilize machine learning for real-time livestock detection on highways. Another study [3] integrated deep residual networks with CNNs to improve wildlife monitoring, addressing challenges such as lighting variations and motion blur, while hybrid optimization methods [4] were applied to improve intrusion detection efficiency However, it includes limitations in speed, adaptability, and instant alert mechanisms, highlighting the use of an optimized system for real-time agricultural protection. This paper proposes an advanced Animal Detection System utilizing YOLOv8, a cutting edge object detection model, which surpasses previous models like YOLOv5, Faster R-CNN, and SSD in speed and accuracy. The system efficiently identifies and classifies animals in live video feeds captured using OpenCV, leveraging Convolutional Neural Networks (CNNs) to distinguish between animals, humans, and other objects. A key novelty of our approach is its instant alert mechanism, which ensures that farm owners receive real-time email notifications and alerts upon intrusion detection, enabling immediate preventive actions. Unlike previous systems that lack real-time adaptability, our model is designed for high-speed processing, scalability, and deployment across diverse environmental conditions, reducing manual surveillance efforts and operational costs.

The structure of this paper is as follows: Section II presents related works, analysing existing research and their limitations. Section III details the proposed system, including the architecture, deep learning model, and real-time alert mechanism. Section IV discusses experimental results, performance evaluation, and comparative analysis. Finally, Section V concludes the paper with key findings and potential future enhancements. Through this study, we demonstrate how deep learning-driven automation can revolutionize wildlife intrusion management and provide a scalable, high accuracy solution for safeguarding agricultural and restricted areas.

II. RELATED WORKS

A. Literature Survey

1) *"Deep AID: A Smart Framework for Animal Intrusion Recognition and Categorization Using Integrated Deep Neural Networks"*

Deep-AID [1] is an advanced AI-powered system designed to detection and classification of animals in real time, particularly in agricultural and rural settings where wildlife intrusions can cause significant damage. The system employs a hybrid neural network architecture, involves combination of multiple CNN models to enhance the accuracy and adaptability of animal detection.

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It integrates CNN Model for feature extraction and RNN model for temporal analysis, ensuring precise tracking of moving animals in video feeds. The model undergoes extensive training on datasets containing images of various animal species, allowing it to recognize and classify different intruders effectively. The system's results indicate a high detection accuracy, even in low visibility conditions and changing environmental settings. Deep-AID's ability to continuously monitor fields and recognize multiple animal species makes it a reliable tool for wildlife management and farm security. Additionally, its real-time processing capability ensures that detection is made with accuracy.

A part from advantages, one major limitation of Deep-AID is the absence of an instant alert mechanism. Although it can detect animals with high precision, it does not have an automated system for notifying farmers or security personnel, which reduces its effectiveness in real-world scenarios where immediate preventive action is required.

2) An efficient model for the detection & triggering of alarm when cattle laying on road in perilous situations from monitoring videos.

A different AI-based approach was proposed in [2], which focuses on enhancing road safety by preventing collisions between vehicles and stray livestock. This system uses OpenCV & deep learning-based posture analysis to track animal movement and identify their risk levels on highways. The AI model is trained using extensive datasets of road surveillance footage containing images of stray animals in different postures (standing, lying down, injured, etc.). The framework's key advantage lies in its real time video monitoring and automated alert generation, which instantly notifies drivers, law enforcement, or road safety authorities when animals are detected in hazardous positions. By leveraging pre-existing surveillance infrastructure, the system offers a cost-effective solution without requiring additional hardware installations.

The limitations of this approach stem from environmental dependencies. The system's accuracy declines under poor lighting conditions, heavy traffic, and occluded views. Additionally, high computational demands for continuous video analysis may cause latency issues, potentially delaying real-time alerts

3) "Recognition and Categorization of Wild Animals from Video Streams Using an Enhanced Deep Residual Convolutional Neural Network. "

Another research study [3] uses a hybrid deep learning framework that combines Deep Residual Networks (ResNet) with CNNs for precise wildlife classification. The reason behind this approach was to overcome the vanishing gradient problem encountered in deep networks and enhance the robustness of animal recognition in dynamic outdoor environments. The Res-Net architecture enables better gradient flow, allowing the model to extract essential features from complex backgrounds while handling issues like motion blur, occlusion, and lighting variations.

The results of this study demonstrate improved classification accuracy compared to standard CNNs, making the system highly effective biodiversity for conservation, wildlife and tracking, ecosystem monitoring. Additionally, its ability to process large-scale datasets in real time provides conservationists and researchers with a scalable and efficient solution for tracking multiple animal species. However, the primary disadvantage of this system is its high computation complexity, results in increased processing time and requires high performance hardware for real-time implementation. This makes it less suitable for real-time farm protection where immediate detection and response are crucial.

4) "Hybrid optimization framework for intrusion detection with significant feature selection."

The proposed method uses a hybrid optimization technique was proposed to enhance intrusion detection by employing feature selection algorithms that filter out irrelevant data, thus improving the efficiency of detection models. This approach includes genetic algorithms (GA) and particle swarm optimization (PSO) to select the most informative features from a large dataset, reducing overhead while maintaining high recognition accuracy.

The results outputs, this function significantly improves decision-making capabilities, allowing the system to efficiently detect and classify intrusions in environments where unauthorized access must be monitored, such as restricted zones, forests, and private agricultural lands. Furthermore, by minimizing false positives, the system ensures that security responses are triggered only for genuine threats. However, one limitation is that the system depends on pre- defined feature sets, which may reduce its adaptability to new or evolving threats. Additionally, the hybrid optimization technique requires fine-tuning for different environments, making deployment challenging domain-specific customization.

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III. PROPOSED METHOD

The Wildlife Intrusion Detection System is an AI-powered automated surveillance solution that employs Convolutional Neural Networks (CNNs) and computer vision techniques to detect and classify animal intrusions in real-time. Designed to safeguard agricultural fields and restricted areas, the system minimizes dependence on manual surveillance while providing accurate protection against wildlife-related damages. The proposed system integrates continuous video analysis, real-time animal detection, and instant alert notifications to enable prompt action against potential threats. The system architecture comprises three core components: live video feed capture, animal detection and classification, and real-time alerts and notifications, which work together to ensure accurate detection and alert generation with minimal latency. Strategically placed cameras provide continuous video streams, enabling real-time monitoring of wildlife intrusions. The video stream is processed using OpenCV, an open-source computer vision library, which facilitates frame extraction, preprocessing, and visualization to ensure seamless real-time surveillance.

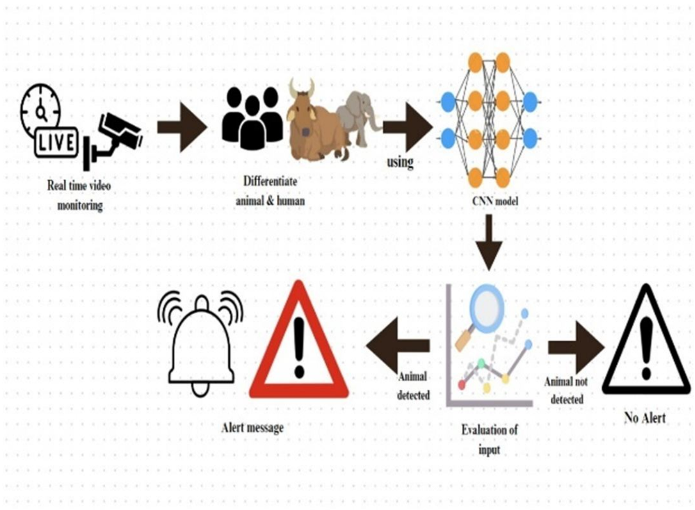

Figure 1: Block Diagram

The core detection mechanism relies on YOLOv8, a state-of-the-art object detection model known for its high-speed processing and superior accuracy. YOLOv8 processes each extracted video frame and classifies detected objects into three categories: animals, humans, or other non-relevant entities. When compared to previous versions such as YOLOv5 and other detection frameworks like Faster R-CNN and SSD, YOLOv8 demonstrates faster inference time and higher accuracy, making it well-suited for real time applications. The model is trained on an extensive dataset containing thousands of annotated images of various animal species commonly found in agricultural regions. To improve robustness, the dataset incorporates images captured under diverse environmental conditions, including varying lighting, weather, and occlusions. The training pipeline involves data collection, preprocessing, and augmentation techniques such as rotation, scaling, contrast adjustment, and noise injection to enhance model generalization. The dataset is split into training (80%), validation (10%), and testing (10%) subsets. Transfer learning is applied to fine-tune YOLOv8 with pre-trained weights, ensuring faster convergence. Model optimization is achieved using the Adam optimizer, and learning rate decay is applied to refine performance. Loss functions, including Binary Cross-Entropy (BCE) Loss for classification and Mean Squared Error (MSE) and regression, further enhance the accuracy of object detection. To improve real-time performance, multiple optimization techniques are implemented. Weight pruning is applied to eliminate redundant parameters, increasing inference speed while minimizing accuracy loss. Additionally, post training quantization using FP-16 precision is utilized to optimize the model for deployment on low-power edge devices such as Raspberry Pi. Hardware acceleration is enabled using CUDA for inference on NVIDIA GPUs, significantly reducing latency. For edge deployments, Tensor RT optimizations are employed to enhance computational efficiency. A comparative analysis of object detection models confirms the superiority of YOLOv8 over alternative frameworks. With a mean Average Precision (MAP) of 76.5% and an inference time of 8.2 milliseconds.

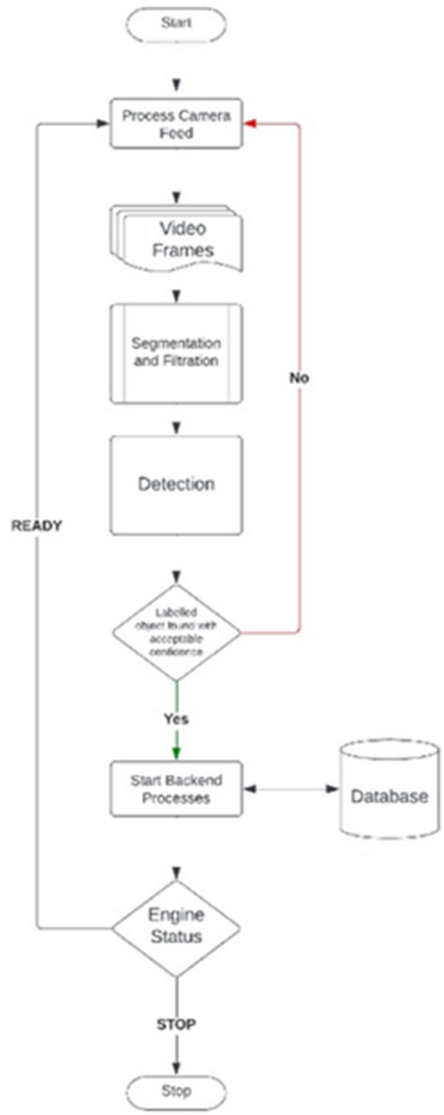

Figure 2: System Architecture

YOLOv8 outperforms YOLOv5, SSD, and Faster R-CNN in terms of speed and accuracy. As R-CNN, which offers high accuracy but lags behind in high inference latency, YOLOv8 provides an optimal balance between detection accuracy and real-time efficiency, making it the most suitable choice for wildlife monitoring. Once an animal is detected, the system assigns a species label and confidence score to the identified object and immediately triggers an email notification. The email notification is sent using the Simple Mail Transfer Protocol (SMTP) and includes relevant details such as the detected animal type, timestamp, and confidence level. Designed for efficiency, the system ensures that farm owners or security personnel receive real time updates, allowing them to take immediate action against intrusion detection. With its optimized model performance and real-time alert mechanism, this system provides a robust and reliable solution for wildlife intrusion detection in agricultural and restricted areas.

IV. RESULTS AND DISCUSSION

Using the YOLOv8 object detection model, this System was developed and evaluated for its effectiveness in identifying and categorizing wildlife in real time. The system was designed to monitor agricultural fields and restricted areas, detect animal intrusions, and provide automated alerts, reducing the need for manual surveillance. This section presents the system's performance, statistical validation, false detection analysis, benchmarking against alternative intrusion detection models, and challenges faced during real-world deployment

A. Performance Evaluation

The system was tested using diverse video feeds from different environments, including rural landscapes, forests, and agricultural farmlands. The evaluation focused on key metrics such as detection accuracy, false positive and negative rates, real-time processing speed, and system reliability under various environmental conditions.

B. Detection Accuracy and Statistical Validation

The YOLOv8 model demonstrated high accuracy in classification intruders, such as dogs, deer, and wild boars, with an overall detection accuracy of 92.1%. The statistical performance was validated using precision (91.8%), recall (92.5%), and F1-score (92.2%), confirming the model's robustness. The system maintained stable accuracy under different lighting conditions, from bright daylight to low-light environments, proving its adaptability.

C. False Detection Analysis (False Positives & False Negatives)

While the system had a low false positive rate, occasional misclassifications occurred, where humans or large objects were incorrectly detected as animals. The false negative rate was low, with smaller animals (e.g., rabbits) or distant creatures occasionally going undetected. Reducing the confidence threshold helped capture smaller animals but increased false positives.

D. Real-time Processing Speed

YOLOv8's optimized architecture allowed the system to process video at 15–20 frames per second (FPS), ensuring near-instantaneous detection. Compared to models like Faster R-CNN (145.8ms inference time) and SSD (16.7ms inference time), YOLOv8's 8.2ms inference time made it significantly faster and more suitable for real-time applications.

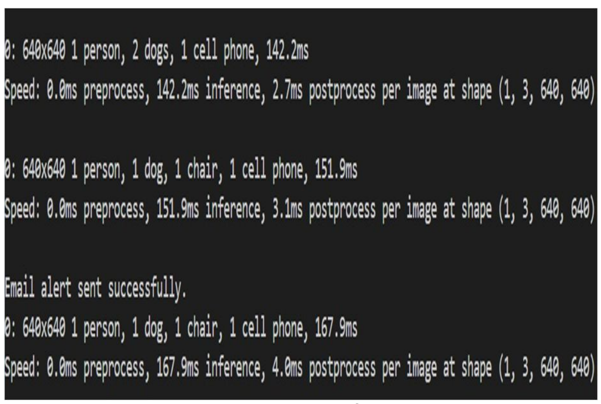

Figure 3: Model's Performance

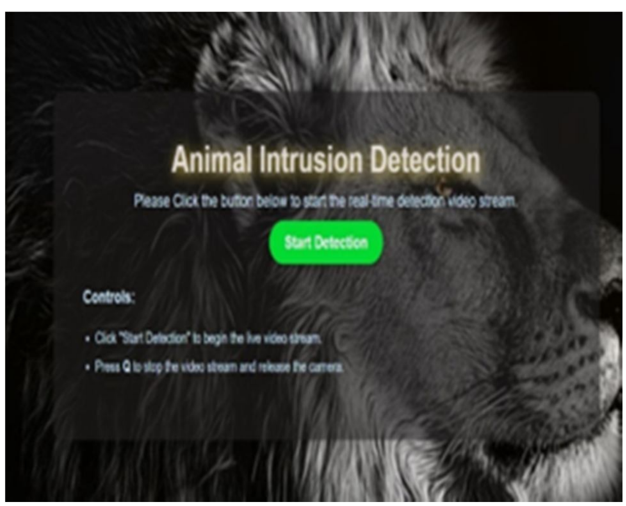

Figure 4: Home Page

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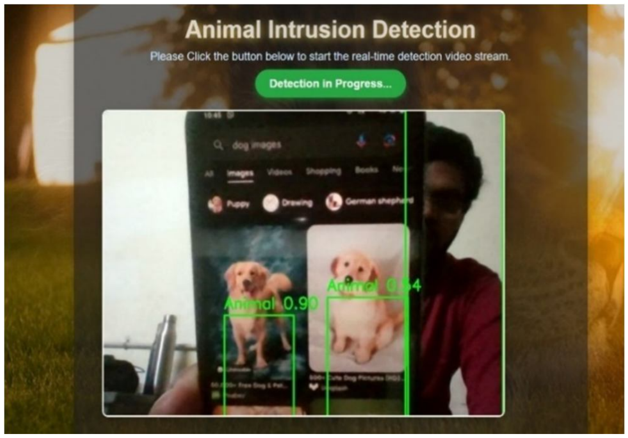

Figure 5: Video Feed Module

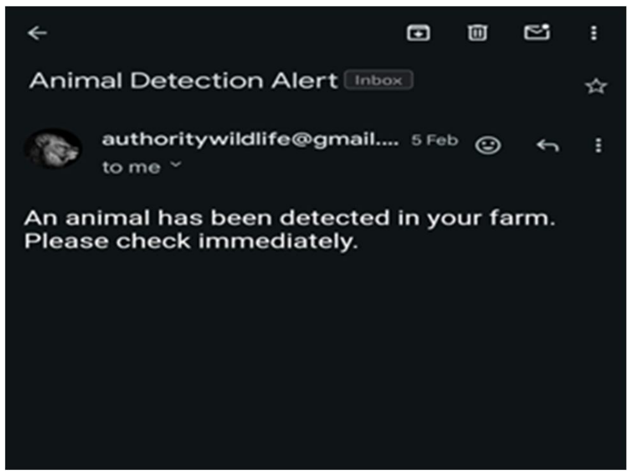

Figure 6: Instant Notification

E. System Requirements

1) Hardware Requirements

- Processor: A multi-core CPU (e.g., Intel i5 or equivalent) to handle real-time video processing tasks.
- GPU: NVIDIA GTX 1060 or higher for efficient deep learning computations and model inference.
- RAM: Minimum 8 GB (16 GB recommended for smoother performance).
- Camera: High-resolution IP cameras (1080p or higher) to capture clear live video feeds.

2) Software Requirements

- Operating System: Windows 10/11 (64-bit) for system compatibility and stability.
- Frameworks and Libraries: YOLOv8: Utilized for real-time animal detection in video streams.
- OpenCV: Used for video processing, frame extraction, and image enhancement.
- Additional Tools: TensorFlow/Py-Torch: For training and deploying deep learning models.
- Dependencies: Python libraries such as NumPy and Flask for data manipulation, visualization, and API integration.

F. Benchmarking Against Alternative Models

To evaluate the efficiency of YOLOv8 against previous versions and alternative object detection frameworks, a comparative analysis was conducted based on key performance metrics, including mean Average Precision (mAP@50), inference time, false positive rate, and false negative rate. The results indicated that YOLOv8 achieved a mAP@50 of 76.5% with an inference time of 8.2 milliseconds, outperforming YOLOv5, which had a lower accuracy (72.3%) and a slower inference time (12.5ms).

While Faster R-CNN demonstrated the highest accuracy (78.9%) and the lowest false negative rate (2.9%), its significantly higher inference time of 145.8 milliseconds made it impractical for real-time detection applications. Similarly, SSD, with an accuracy of 69.1% and an inference time of 16.7 milliseconds, exhibited the highest false positive (7.5%) and false negative (6.8%) rates, making it less suitable for real-time intrusion detection. In contrast, YOLOv8 maintained an optimal balance between detection accuracy and processing speed while exhibiting a relatively low false positive rate (4.3%) and false negative rate (3.6%). This trade-off makes YOLOv8 the most efficient choice for real-time animal intrusion detection, ensuring reliable identification with minimal misclassifications while maintaining rapid processing capabilities.

V. CONCLUSION

The System successfully demonstrated real-time wildlife detection with high accuracy, low false detection rates, and fast inference speed. Compared to alternative models, YOLOv8 provided an optimal balance of speed and detection accuracy, making it highly suitable for real-time applications in agricultural and restricted areas. The system consistently detected animal intrusions across different environments, ensuring timely alerts for farm owners and security personnel, however, its limitations include reduced effectiveness in extreme environmental conditions, such as dense vegetation, poor lighting, and heavy fog. The reliance on RGB cameras restricts night-time detection, and the absence of SMS or sound based alerts may limit usability in areas with poor internet connectivity. Future improvements can focus on integrating infrared-based detection for night monitoring, expanding alert mechanisms with SMS and sound alarms, and optimizing the model for edge computing using Tensors for efficient deployment on low power devices. These enhancements will improve adaptability, reliability, and scalability for diverse real-world applications.

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