DEEP LEARNING BASED REAL-TIME DETECTION OF MONKEY AND BISON INTRUSION IN FARM FIELD AND AUTONOMOUS HUMANE REPELLENT SYSTEM FOR CROP PROTECTION

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Keywords:

Deep Learning, YOLOv8, Swin Transformer, Animal Detection, Humane Repellent System

Introduction:

Human-wildlife conflict is a growing concern, especially in rural and agricultural regions where animals such as monkeys and bison frequently enter human settlements, causing damage to crops, property, and sometimes posing threats to human safety. Traditional methods of monitoring and preventing such intrusions are often manual, inefficient, and may harm the animals.

With advancements in artificial intelligence and computer vision, automated systems can be developed to detect and respond to wildlife presence in real time. Deep learning-based object detection models, particularly YOLO (You Only Look Once), have shown high accuracy and speed in identifying objects in live video streams.

This project aims to develop a real-time animal detection system using YOLOv8 that can identify monkeys and bison from video input and trigger a humane repellent mechanism. The system also sends alert messages to users, enabling timely action. The proposed solution focuses on reducing human effort, minimizing harm to animals, and improving safety and efficiency in monitoring wildlife activity.

Objectives:

1. To develop a real-time detection system for monkeys and bisons
2. To improve detection accuracy using YOLOv8 and Swin Transformer
3. To design a humane deterrent mechanism without harming animals
4. To implement an alert system for real-time farmer notification.
5. To reduce crop damage and manual monitoring efforts

Methodology:

The proposed system follows a modular pipeline consisting of input acquisition, preprocessing, detection, post-processing, and alert generation. Video input is captured using a camera and converted into frames. Each frame undergoes preprocessing steps such as resizing and normalization to match the input requirements of the deep learning model.

The detection is performed using a hybrid architecture combining YOLOv8 and a Swin Transformer. YOLOv8 provides fast object detection and bounding box prediction, while the

Swin Transformer enhances contextual feature extraction, improving detection accuracy in complex environments.

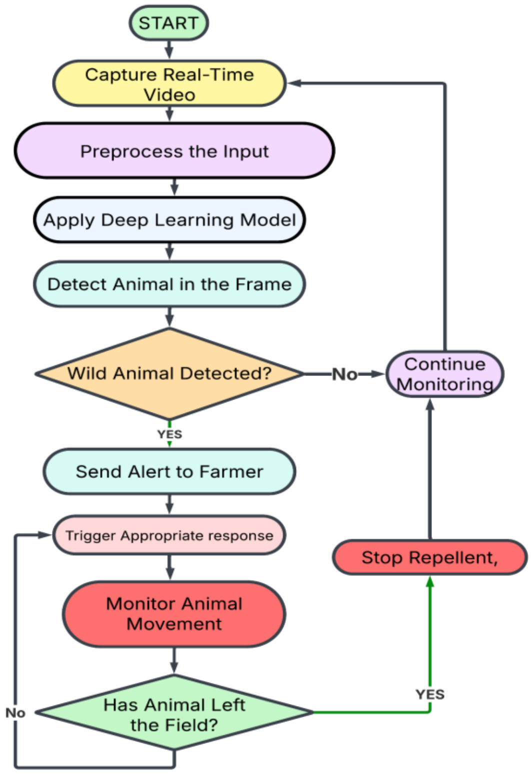


Figure 1: Flow Chart

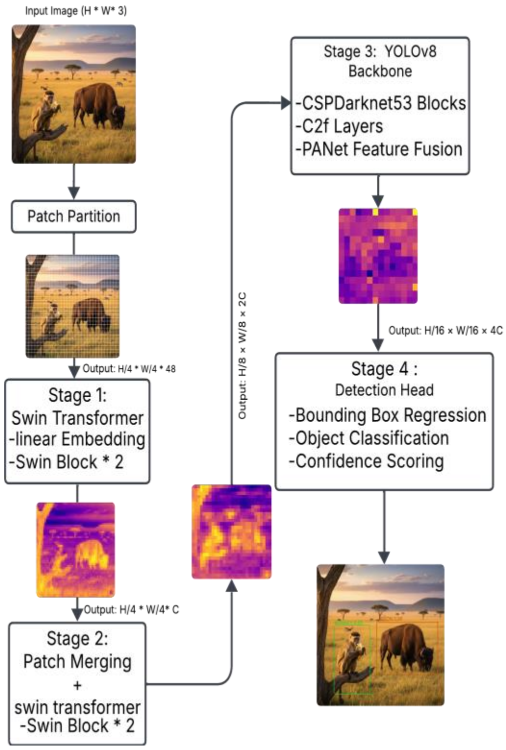
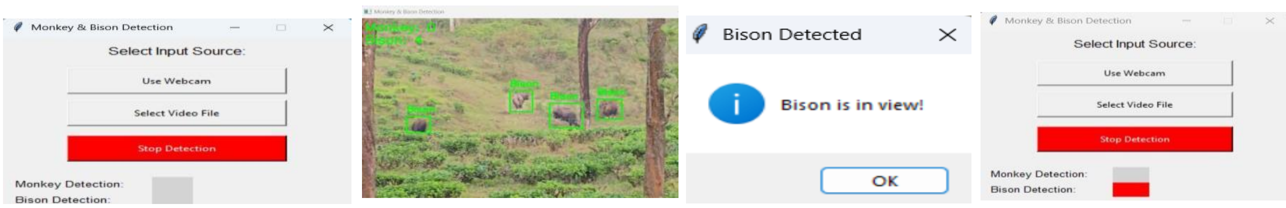


Figure 2: YOLOv8–Swin-Tiny Model Architecture

Once an animal is detected, the system activates a humane deterrent such as sound or light alerts. Simultaneously, notifications are sent through a graphical user interface to inform the user. The system ensures real-time detection, high accuracy, and efficient monitoring of wildlife intrusion.

Result and Conclusion:

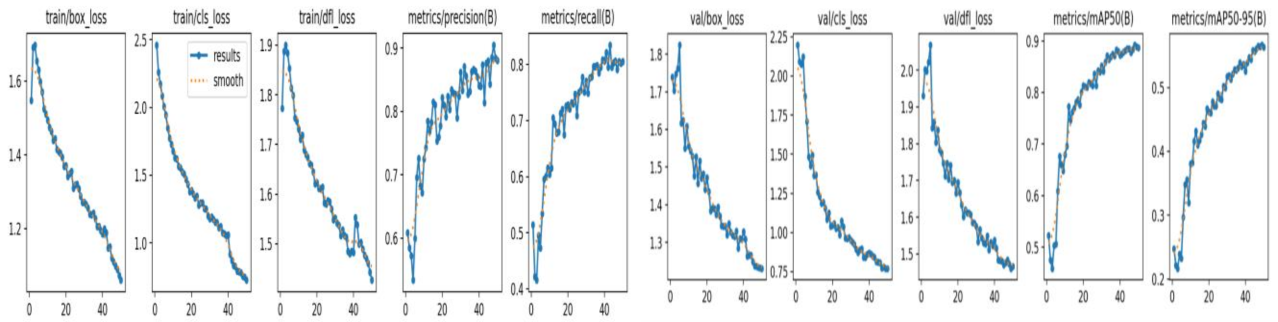
The system successfully detects monkeys and bison in real-time with high accuracy. The model achieved a precision of 0.881, recall of 0.806, and mAP@50 of 0.896 indicating strong detection performance. The integration of the Swin Transformer improves detection performance in challenging conditions such as occlusion and varying lighting environments.



(a) (b) (c) (d)

Figure 3: Real-time Detection and Repellent System GUI
(a) Initial GUI (b) Real-time Bison Detection (c) Alert Module Activation (d) Popup Notification for Bison

The system effectively triggers alerts and activates humane deterrent mechanisms through a graphical interface, ensuring timely response. In conclusion, integration of the Swin Transformer improves detection performance in challenging conditions such as occlusion and varying lighting.



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Figure 4: YOLOv8–Swin Training Results
(a–c) Training losses (box, cls, dfl) (d–e) Precision and recall (f–h) Validation losses (i–j) mAP@50 and mAP@50–95 metrics)

Table I: Comparative Analysis of Existing Methods

Paper Title	Approach Used	Obtained Results
An Accurate and Fast Animal Species Detection System for Embedded Devices	Modified YOLOv2 with multi-level feature merging, pruned convolutional layers, and DCLs	~85.5% on Core i7 setup
Design, Development and Evaluation of an Intelligent Animal Repelling System for Crop Protection Based on Embedded Edge-AI	Virtual-fence system combining vision (YOLO/Tiny-YOLO) and ultrasound.	YOLOv3: mAP 82.5%, Recall 64%.
A Practical Animal Detection and Collision Avoidance System Using Computer Vision Technique	Used a simple computer vision–based animal detection with distance estimation for highway safety	Achieved ~82.5% detection accuracy
Proposed YOLOv8–Swin Hybrid Model for Farm Intrusion Detection	YOLOv8 integrated with Swin Transformer and weighted feature fusion for motion and visual features	mAP@50 = 0.89, Precision = 0.88, Recall = 0.82

The system effectively triggers alerts and humane deterrents through a graphical interface.

Project Outcome & Industry Relevance

The project results in a functional prototype capable of real-time animal detection and alert generation. It has applications in agriculture, forest monitoring, and smart surveillance systems.

Farmers can use this system to protect crops without continuous monitoring, reducing labor and improving efficiency. Forest departments can utilize the system to monitor wildlife movement and prevent conflicts.

The project aligns with current industry trends in artificial intelligence, computer vision, and smart agriculture. Its low-cost and scalable design makes it suitable for deployment in rural areas.This system contributes to sustainable farming practices and promotes ethical wildlife management.

Working Model vs. Simulation/Study: The project is implemented as a working model with real-time detection and GUI-based alert system, tested in a simulated environment.

Project Outcomes and Learnings

1. Gained practical experience in deep learning and object detection
2. Learned implementation of YOLOv8 and Swin Transformer models
3. Developed skills in dataset collection and annotation
4. Implemented real-time detection and alert systems
5. Improved understanding of AI applications in agriculture

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Future Scope:

1. The system can be extended to detect more animal species and improve versatility. Accuracy can be enhanced using larger and more diverse datasets.
2. Integration with IoT devices and automated systems can improve real-world deployment. Mobile applications can be developed for real-time monitoring.
3. Future improvements include edge deployment for faster processing and night detection using infrared cameras.
4. The system can be scaled for large agricultural areas and integrated with smart farming technologies.