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WildShield- An Intelligent Wild Life Intrusion and Detection Alert System

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Abstract— **In this paper, a YOLOv8-based deep learning model implemented on a Raspberry Pi 5 is used to construct a real-time wild animal detection and alert system. Enhancing human safety and minimizing property damage in areas vulnerable to wild animal infiltration are the system's main goals. A custom-trained YOLOv8 model tailored for the Raspberry Pi platform processes live video captured by a webcam in real time. To guarantee precise identification and classification, the model is trained on a labeled dataset that includes pictures of particular wild animals, such as wild boar, elephants, tigers, and leopards. The technology creates a dual-response mechanism when it detects a target animal: a high-intensity sound output via a Bluetooth speaker to repel the animal and an audible buzzer alarm to inform surrounding humans. The suggested system can successfully identify and categorize several wild animal species in real time with adequate accuracy, according to experimental results, making it appropriate for use in rural and forest-edge settings. The proposed system achieved 92% detection accuracy, 50–60 ms inference time, and AUC values above 0.90 for all animal classes.**

Keywords— Wildlife Intrusion, Deep Learning, Object Detection, YOLO, IoT, Raspberry Pi 5, Human-Wildlife Conflict.

I. INTRODUCTION

Conflict between humans and wildlife has become a major issue in Kerala, endangering both human life and the viability of agriculture. The seriousness of the problem is demonstrated by the fact that 486 human deaths from attacks by wild animals were reported between 2019 and 2024. Since 2014, 149 deaths have been reported in the Wayanad area alone, suggesting a chronic and confined risk. Frequent wildlife incursions have resulted in significant agricultural damage in addition to fatalities, especially for crops like coconut, paddy, and tuber kinds that are extremely susceptible to animal raids. Sadly, two old people died in different situations in March 2024, increasing the overall number of fatalities to 14 in just the first 65 days of the year. The development of the suggested intelligent detection and warning system was prompted by these data, which highlight the critical need for an effective, real-time monitoring and alarm system to reduce interactions between people and wildlife.

In this paper, a YOLOv8-based deep learning model implemented on a Raspberry Pi 5 is used to construct a real-time wild animal detection and alert system. Improving human safety and reducing property damage in places susceptible to wildlife infiltration are the main goals. A custom-trained YOLOv8 model optimized for embedded deployment processes live video captured by a webcam in real time.

To guarantee precise identification and classification, the model is trained on a labeled dataset that includes pictures of particular wild animals, such as wild boar, elephants, tigers, and leopards. When the system detects a target animal, it launches a dual-response mechanism that includes a high-intensity sound output via a Bluetooth speaker to repel the animal and an audible buzzer alarm to inform nearby persons. The suggested method is a workable option for implementation in rural and forest-border areas since it shows efficient real-time detection and classification of several wild animal species. A custom dataset for the detection of wild animals was used to train the YOLOv8 model. Images from four classes—wild boar, elephant, tiger, and leopard—make up the dataset. Images were collected from publicly available sources and open datasets to ensure diversity in environmental conditions such as lighting, background, scale, and orientation.

Traditional methods include

1. Infrared and motion sensors: These sensors are used to detect movement in a predefined area. While inexpensive and easy to install, they tend to generate many false positives, especially when triggered by wind-blown vegetation, rain, or small animals like rodents and birds. Their limited sensing range and inability to classify objects accurately make them less suitable for real-time wildlife detection.

2. Camera traps: These are passive infrared cameras that are triggered by motion. Although highly effective for research and monitoring purposes, they are not suitable for real-time alerting as they require manual data retrieval and

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analysis. Additionally, their effectiveness diminishes in low-light conditions unless equipped with infrared flash, which increases cost.

3. Acoustic sensors: These devices can detect sounds specific to certain species, such as elephant trumpets or tiger roars. However, they are highly susceptible to ambient noise, making them unreliable in environments with high wind, rain, or human activity. Moreover, not all species produce identifiable sounds, limiting their scope.

4. Electric and solar-powered fences: These are commonly used to physically deter animals from entering specific zones. While they can be effective, they are expensive to install and maintain. In many cases, large animals like elephants can damage or bypass these fences, and there is also a risk of injury to both animals and humans.

5. Manual patrolling and community monitoring: In many regions, communities organize patrols or employ watchers to monitor for wildlife. Although this method provides a human judgment component, it is labor-intensive, inconsistent, and cannot ensure 24/7 coverage. Human error, fatigue, and delays in communication further limit its effectiveness.

Limitations of Traditional Methods are

- High false alarm rates: Particularly for motion and infrared sensors, leading to desensitization or alarm fatigue among users.
- Lack of real-time processing: Most systems, like camera traps, do not provide instant alerts.
- Poor object classification: Inability to distinguish between domestic animals, humans, and wild animals.
- High operational costs: Systems such as electric fences or human patrolling require constant maintenance and resource allocation.
- Limited scalability and adaptability: Traditional systems are hard to scale across large terrains and often fail to adapt to new animal behavior or environmental conditions.
- Privacy and safety concerns: Human patrolling in forest-edge areas can lead to fatal encounters with wild animals.

Given these drawbacks, there is a growing interest in automated systems that leverage advancements in computer vision, artificial intelligence, and connected hardware to provide intelligent and responsive solutions for wildlife monitoring.

A. Literature Survey

In order to increase object detection accuracy and efficiency, Depuru et al. [1] suggested a Raspberry Pi-based animal intrusion detection system using Fast R-CNN. By sharing convolutional calculations and cutting down on training and inference time, Fast R-CNN improves performance. Real-time monitoring in agricultural fields is made possible by the system, although performance on embedded devices is constrained by its computing complexity and reliance on region proposal techniques. The combination of IoT and deep learning greatly increases detection scalability and reliability when compared to conventional methods.

Using YOLOv4, A. Sharma and Kumar [2] created a Raspberry Pi-based wild animal detection system that allows for faster and more accurate real-time object detection. YOLOv4 achieves outstanding performance in object identification tasks by including sophisticated architectural elements as CSP, SPP, and PAN. The technology is appropriate for agricultural surveillance since it records live footage and sends out notifications when it detects animals. Although there are certain trade-offs in detecting accuracy, lightweight versions like YOLOv4-Tiny further improve deployment feasibility on embedded platforms.

A real-time animal detection system that combines AI and IoT for agriculture monitoring was proposed by Patil et al [3]. To enable remote surveillance and alarm creation, the system makes use of camera modules and Internet of Things connectivity. While IoT improves scalability and real-time connectivity, AI-based object detection increases robustness and accuracy. But issues like power consumption, edge deployment limitations, and network latency still exist. The method performs noticeably better than conventional sensor-based intrusion detection systems.

The rising issue of animal intrusions in agricultural fields has been tackled by Kathir et al. [4] who introduced an Animal Intrusion Detection System using the YOLOv8 object detection algorithm. The purpose of the system was to help detect the presence of animals in farms and notify farmers with alerts, which would minimize damage to crops and conflict between farmers and wild animals. The authors chose YOLOv8 because of its remarkable speed and accuracy compared to the previous generation of YOLO. The proposed framework is continuously monitoring agricultural environment through camera-based surveillance and real-time animal detection. Once an animal is detected, it triggers warning systems and sends notifications to relevant persons. The research showed that YOLOv8 has a strong capability of fast and accurate object detection that makes it well suited for real-time monitoring applications in the field of wildlife. The focus of the work was mainly on identification and alert generation for animals and only a small amount of work went into embedded edge deployment and deterrence mechanisms.

Govardhan et al. [5] created a wildlife tracking and anomaly detection real-time system with the help of YOLOv8. The system performed continuous surveillance of wildlife movements and detected unusual animal behaviour using video analysis. The study showed that YOLOv8 is useful for real-time wildlife surveillance and tracking. The work mainly focused on monitoring and anomaly detection, while the proposed system is concerned with the detection of wildlife intrusion, the deployment of the system on Raspberry Pi 5, and the creation of automated alerts to prevent human–wildlife conflicts.

Chappidi and Sundaram [6] proposed a novel animal detection framework using Cascaded YOLOv8 using adaptive pre-processing and feature extraction. The proposed method enhanced the image quality of the proposed images and extracted the features of the images before classification, which improved the accuracy and robustness of the detection. The study proved the benefits of advanced pre-processing techniques in enhancing wildlife

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detection performance. The proposed system, however, emphasized more on the aspect of detection of wildlife intrusion in real time, deployment of raspberry pi 5, and generation of an automatic alarm for the field application, while the work mainly concentrated on the accuracy of detection.

Lekhadia et al. [7] developed an edge computing-based wildlife detection and alert system using YOLOv8 on Raspberry Pi 5. The system performed real-time animal detection and generated alerts without requiring cloud connectivity, demonstrating the effectiveness of edge AI for wildlife monitoring applications. The study highlighted the capability of Raspberry Pi 5 to support real-time YOLOv8 inference in resource-constrained environments. However, the work primarily focused on detection and notification, whereas the proposed system additionally incorporates buzzer alerts and audio deterrence mechanisms to actively reduce wildlife intrusions.

May et al. [8] introduced POLO, a point-based multi-class animal detection framework designed to reduce the annotation effort required for wildlife datasets. The proposed method demonstrated effective detection of multiple animal species while relying on point-based annotations rather than traditional bounding boxes. The study highlighted an efficient approach for large-scale wildlife monitoring and dataset development. However, the work focused primarily on detection methodology and annotation efficiency, whereas the proposed system concentrates on real-time wildlife intrusion detection, Raspberry Pi 5 deployment, and automated alert generation for practical field applications.

Previous research has shown that deep learning models, such as the YOLO family, can successfully be used for wildlife monitoring, animal detection, and intrusion prevention. With recent developments in edge computing, these models can be deployed to resource-limited devices like Raspberry Pi, making real-time monitoring systems more feasible and affordable. This paper works on this gap by introducing the complete wildlife intrusion alert system that is based on YOLOv8 and Raspberry Pi 5 and can detect any animal and send automatic response in agriculture and forest-border environment.

II. TECHNOLOGY IN GENERAL

AI-based wild animal identification and prevention requires a number of critical technologies. This project develops a real-time animal detection and alert system by combining deep learning, computer vision, and sound-based preventative measures.

The main technological elements utilized are listed below

1. Object detection and computer vision

Computer vision is crucial for recognizing wild animals in video feeds because it allows machines to comprehend and process visual information. Object detection is a subset of computer vision that involves locating and classifying objects in images or video streams. Computer vision allows the system to work autonomously and in real-time on the edge device (Raspberry Pi 5) without the requirement for internet connectivity or cloud processing. This makes it extremely ideal for remote locations like farms or forest edges where connectivity is poor.

2. YOLOv8 (You Only Look Once, version 8)

YOLOv8 is a deep learning model, which is advanced and optimized for real-time object detection. It deals with a full image in a single pass and is therefore quicker and more efficient than other techniques.YOLOv8 can be pre-trained on large databases and fine-tuned to detect particular wild animals. The most important application of YOLOv8 in this framework is its speed in detecting and classifying animals in real time, which is essential for the timely alerting and response. Upon detection of an animal in the field of view of a camera, YOLOv8 delivers the detection output—bounding boxes, labels, and confidence scores—that are utilized to initiate automated responses. These include sounding a buzzer to alert humans and a blasting sound over a Bluetooth speaker to deter the animal.

3. Audio-based deterrence

Audio-based deterrence is an established technique to frighten wild animals away. Various wild animals are responsive to dissimilar sounds, and AI-based adaptive deterrents have proved to be an efficient solution.

A. Block Diagram

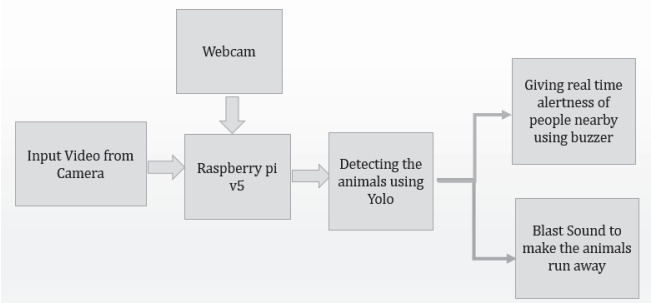


Figure 1: Block Diagram of the Proposed System

- Input Video via webcam - A USB camera or Raspberry Pi Camera Module is attached to the Raspberry Pi 5.Resolution and frame rate can be specified to maximize performance. The frames are read one by one from the video stream.
- Raspberry pi v5- A high-performance single-board computer and improved I/O features over its ancestors. It is designed for high-performance computing, AI applications, and real-time processing, making it an excellent choice for deploying YOLOv8-based wild animal detection systems. It is used as the central processing unit to execute the object detection model, handle webcam input, and manage output devices such as buzzers and speakers.
- Detection of animals using YOLO - YOLOv8 is a deep learning model, which is advanced and optimized for real-time object detection. It deals with a full image in a single pass and is therefore quicker and more efficient than other techniques.YOLOv8 can be pre-trained on large databases and fine-tuned to detect particular wild animals. It balances speed and precision and is ideal for deployment onto resource-limited devices such as Raspberry Pi.

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- Giving a blast or ultrasonic sound to make the animal run away - Blast Sounds (Loud Noises) – Abrupt, loud sounds such as gunshots, firecrackers, or Blast Sound: A high-powered speaker plays pre-recorded sounds when an animal is in the vicinity.
- Giving real time alertness using buzzer: A buzzer alert system gives immediate alerts when a wild animal is detected. This aids nearby humans to take instant action and remain safe. Trigger Alert: When an animal is detected, the Raspberry Pi 5 triggers a buzzer via its GPIO pins. Buzzer Sound: The buzzer sounds a high-pitched alarm, alerting humans nearby.

B. Hardware Implementation

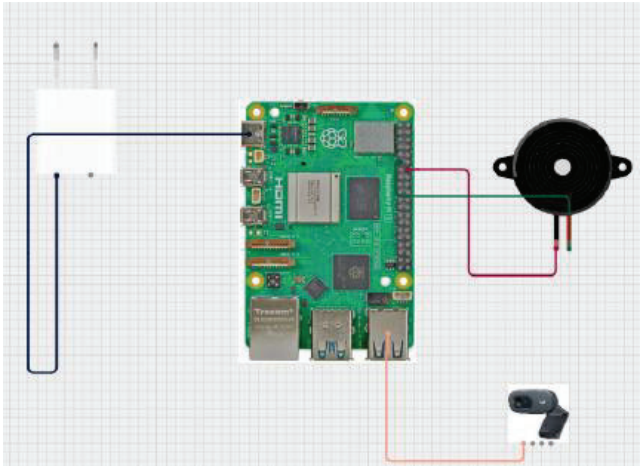


Figure 2: Circuit Diagram

The Wild Animal Entry Alert System functions in a real-time setting, employing a Raspberry Pi 5, webcam, YOLOv8 object detection model, and an alert mechanism (buzzer and frequency-based sounds). An in-depth explanation of how the system works is outlined below.

1. Capturing Live Video Feed

- A webcam is attached to the Raspberry Pi 5, taking real-time video frames perpetually.
- The camera resolution is tuned to process faster
- The frames that are captured are processed by applying OpenCV, which supports reading and showing video feeds more efficiently.
- The frames are captured continuously to provide uninterrupted monitoring of the environment.

2. Object Detection Using YOLOv8

Every frame that is captured goes through the processing of the YOLOv8 (You Only Look Once v8) object detection model. The model has been trained using a custom dataset to identify four particular wild animals: Elephant, Tiger ,Leopard, Wild Boar.YOLOv8 operates in real-time, rapidly detecting objects and outlining bounding boxes around recognized animals. If no wild animal is found, the system continues monitoring, constantly processing new frames without sending out any alerts.

All images were manually annotated using bounding boxes to accurately label the position of animals within each frame. To guarantee accurate evaluation and model generalization, the dataset was split into training, validation, and testing sets. Additionally, to increase robustness in practical situations, data augmentation methods such brightness variation, rotation, scaling, and horizontal flipping were used.

3. Triggering the Alert System

When a wild animal is found, the system retrieves

- The animal's class name (e.g., tiger, elephant, etc.).
- The confidence score (chance of accurate detection).
- When the confidence score is over 50%, the system concludes that there is a wild animal.
- In order to alert humans and repel the animal, the system activates a buzzer powered by the Raspberry Pi.
- The buzzer produces a loud noise, giving a prompt warning to farm workers or local residents.

C. Algorithm

- Step 1: Initialize the System. Load the YOLO model (best.pt). Initialize pygame for sound alerts. Define sound files for different animals. Setup GPIO for buzzer output.
- Step 2:Initialize Camera. Open the webcam (cv2.VideoCapture(0)). Set camera properties (resolution, FPS, buffer size)
- Step 3: Start Frame Processing. Continuously capture frames from the webcam.
- Step 4: Run YOLO Model. Pass the frame through the YOLO model for object detection.
- Get detection results: class ID, confidence, and bounding box.
- Step 5: Process Detections. Extract detected animal names. If confidence > 0.5, check if the animal is new. If new: Play the corresponding sound for the detected animal. Activate the buzzer for alert
- Step 6: Draw Bounding Boxes. Scale bounding box coordinates back to the original frame size.
- Draw a rectangle around detected animals. Display class name and confidence score.
- Step 7: Display Results. Show the processed frame in a window. Check if the user presses ‘q’ to quit.
- Step 8: Loop Continuously. Repeat frame capture, detection, and alerting. Run the process in a separate thread for better performance.
- Step 9: Exit & Cleanup. Release the camera. Close all OpenCV windows. Stop pygame sound processing. Release GPIO resources.

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D. Flow Chart

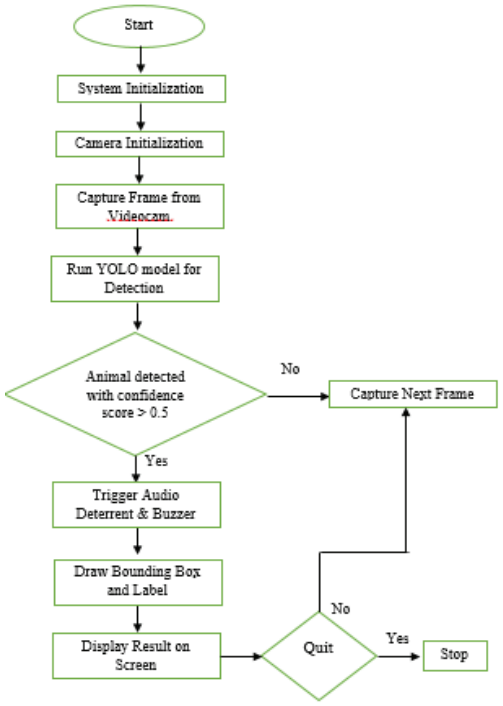


Figure 3: Flowchart of the proposed wildshield system

III. Results and Discussions

YOLOv8, a webcam, and a Raspberry Pi 5 were used to successfully create the Wild Life Intrusion System. A specific dataset was used to train the YOLOv8 model. With an average inference time of roughly 50–60 ms per frame, the system demonstrated real-time detection throughout testing, allowing for quick and responsive operation. Although performance varied slightly based on illumination conditions and object distance, the model consistently detected target animals with an detection accuracy of 92%. The system successfully activated a buzzer sound to warn people when an animal was detected within the camera's frame. At the same time, it used a Bluetooth speaker to make a loud noise to frighten the animal.

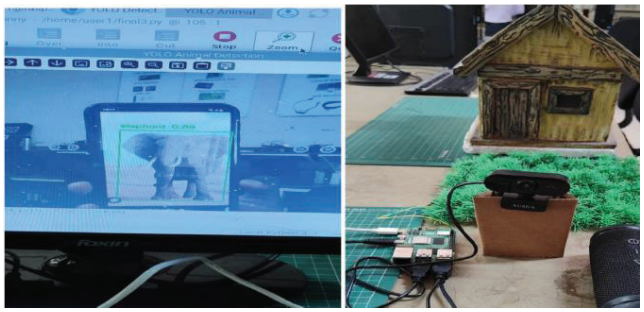


Figure 4: Detection of Wild Animal and Implemented System Model

IV. Conclusion and Future Scope

The potential of edge AI in remote, rural locations with inadequate internet connectivity is demonstrated in this paper. The Raspberry Pi 5 reduces cloud-based computing and provides fast reaction times by managing the entire system locally. This project offers an affordable and efficient method for early animal detection and deterrence using a Raspberry Pi 5 with YOLOv8. In high-risk areas, the device can prevent wildlife intrusions and reduce human-wildlife conflicts.

The future scope of the project include

- Integration with cloud-based monitoring for remote alert: The system can be powered by solar panels for placement in remote locations without reliable energy, guaranteeing continuous operation with little maintenance.
- Integration with IoT and Mobile Alerts: When a wild animal is found, the system can be improved to instantly notify farmers, forest officials, or local authorities by SMS, WhatsApp or mobile apps. Even when users are far away, this provides an additional degree of security and awareness.
- Use of infrared cameras for nighttime detection: By including thermal or infrared cameras, the system will be able to identify creatures at night or in low light, which is when a lot of wild animals are most active.

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