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Prevention of wild life collision in railway track

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Abstract
The rapid expansion of railway infrastructure in India has significantly improved transportation efficiency; however, it has also led to an increase in wildlife-train collisions (WTCs), resulting in serious ecological consequences. Railway tracks passing through forest and wildlife zones disrupt natural habitats, causing fragmentation and forcing animals into dangerous crossings. This threatens wildlife populations and creates operational challenges for railway systems, including train delays and infrastructure damage.
To address this issue, this project proposes an efficient wildlife monitoring system using computer vision and deep learning techniques. The system employs the YOLO (You Only Look Once) object detection model to identify humans and animal species such as elephants, lions, giraffes, zebras, and cheetahs in real-time. Integrated with Arduino-based hardware and camera modules, the system continuously monitors railway surroundings near forest areas. When animals or humans are detected near the tracks, alerts are sent to authorities through communication modules, enabling timely preventive action.
This system provides a proactive monitoring mechanism to reduce wildlife fatalities, improve railway safety, and support ecological conservation. It demonstrates the effective use of artificial intelligence and embedded systems in solving real-world environmental problems and promoting safer railway infrastructure.

Keywords: Wildlife-train collisions (WTC), railway safety, wildlife monitoring, computer vision, deep learning, YOLO object detection, arduino-based system, real-time detection, animal detection, artificial intelligence

Introduction
Railway transportation has become an essential component of modern infrastructure, enabling efficient movement of passengers and goods across vast geographical regions. In countries like India and many others worldwide, railway networks often traverse forest areas and wildlife habitats. While this expansion has improved connectivity and economic growth, it has also introduced unintended consequences, particularly in the form of wildlife–train collisions (WTCs).
Wildlife–train collisions represent a serious and growing concern, as they lead to significant loss of biodiversity and disrupt ecological balance. Unlike human-related railway accidents, animal fatalities often remain underreported and insufficiently studied, despite their long-term environmental impact.
The fragmentation of natural habitats due to railway tracks forces animals to cross these pathways, increasing the likelihood of fatal encounters. Additionally, such incidents can result in damage to railway infrastructure, operational delays, and potential risks to passenger safety.
One of the major challenges in mitigating these collisions is the lack of effective real-time monitoring and early warning systems. Traditional methods, such as manual surveillance or static barriers, are often inefficient, labor-intensive, and not scalable across large forest regions. Furthermore, environmental conditions such as low visibility, dense vegetation, and nighttime operations further complicate detection and prevention efforts.
Recent advancements in artificial intelligence, computer vision, and embedded systems offer promising opportunities to address this issue through automation and intelligent monitoring. By leveraging these technologies, it is possible to develop systems capable of detecting wildlife presence accurately and providing timely alerts to railway authorities.
This work focuses on developing an intelligent and automated wildlife monitoring solution aimed at reducing animal–train collisions. The proposed approach integrates real-time detection, communication, and preventive mechanisms to enhance railway safety while supporting wildlife conservation. By combining technological innovation with environmental responsibility, this study contributes to the development of sustainable and safer railway infrastructure.

Literature Survey
Various research studies have been conducted to detect animals using computer vision and deep learning techniques. Early approaches primarily focused on image segmentation and feature extraction methods. Zhang *et al.* proposed a system using multi-level iterative graph cut for segmenting animals from camera trap images. The system utilized AlexNet and Histogram of Oriented Gradients (HOG) for feature extraction.
Yousif introduced a method combining deep learning classification with dynamic background modeling to detect animals and humans in cluttered environments. This approach improved detection efficiency by generating region proposals. Similarly, Kellenberger *et al.* employed Unmanned Aerial Vehicles (UAVs) integrated with a custom Convolutional Neural Network (CNN) model for wildlife monitoring, though the system showed comparatively lower performance due to environmental challenges.
More advanced deep learning techniques have demonstrated improved performance. Norouzzadeh *et al.* applied deep neural networks on the Snapshot Serengeti dataset for species identification and wildlife monitoring. Parham implemented YOLO-based object detection for animal

localization and classification to improve detection speed and efficiency.

In addition to deep learning approaches, traditional machine learning methods have also been explored. Matuska utilized SIFT and SURF feature extraction techniques combined with a Support Vector Machine (SVM) classifier for detecting animals. Sharma applied cross-correlation filters for template matching to recognize animal shapes and patterns. However, most of these systems primarily focus on detection and classification tasks. They lack integration with real-time monitoring systems and do not provide mechanisms for early warning or collision prevention in railway environments.

The proposed system presents an intelligent and automated solution for detecting and preventing wildlife–train collisions. Unlike existing systems, which are limited to detection, this approach integrates real-time monitoring, object detection, and alert generation. The system utilizes Deep Convolutional Neural Networks
(DCNN), particularly YOLO-based models, to detect and localize animals near railway tracks. Cameras are deployed in high-risk areas to continuously monitor the surroundings. When an animal is detected, the system processes the information in real time and generates alerts to railway authorities.

This integrated approach addresses the limitations of existing methods by enabling timely intervention, thereby reducing collision risks and improving both railway safety and wildlife protection.

Table 1: Literature Review Summary

Author(s)	Year	Method/Algorithm	Findings
Zhang *et al*.	2019	Graph Cut + AlexNet + HOG	Achieved effective animal detection and segmentation using graph-based and feature extraction methods.
Yousif	2020	Deep Learning + Background Modeling	Improved detection of animals and humans in complex and cluttered environments using deep learning and background modeling.
Kellenberger *et al*.	2020	UAV + CNN	Enabled aerial wildlife monitoring using UAVs integrated with CNN models.
Norouzzadeh *et al*.	2018	Deep Neural Networks	Provided efficient species identification using deep neural networks on large wildlife datasets.
Parham	2021	YOLO Object Detection	Enabled real-time animal detection and localization using YOLO-based object detection.
Matuska	2019	SIFT + SURF + SVM	Implemented feature-based animal detection using SIFT, SURF, and SVM techniques.
Sharma	2020	Template Matching	Applied template matching techniques to recognize animal shapes using cross-correlation filters.

Methodology

1. System Overview

The proposed system is designed to detect and prevent wildlife–train collisions using an integrated approach that combines computer vision, embedded systems, and wireless communication. The system continuously monitors railway tracks in forest and wildlife-prone areas using camera modules and sensors. Upon detecting the presence of animals or humans near the tracks, it generates real-time alerts and activates preventive mechanisms.

2. System Architecture

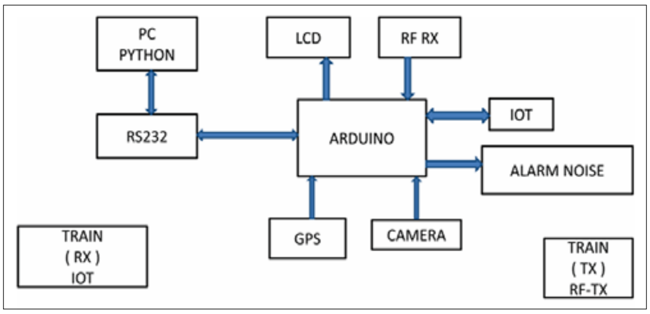

Fig 1: System Architecture of Wildlife Collision Prevention System

As shown in Fig. 1, the system architecture consists of a processing unit, sensing unit, communication module, and alert/display components that work together to detect animals and generate warnings. Figure 2 illustrates the overall system architecture of the proposed wildlife collision prevention system used near railway tracks.

The system begins with the sensing and detection unit, where sensors and camera modules continuously monitor the railway track area. When movement is detected near the track, the captured data is transmitted to the processing unit, which is connected to a PC or microprocessor system. The PC processes the captured data using an object detection model to identify the presence of animals or humans.

The processed information is then transmitted through a Radio Frequency (RF) communication module, where the RF transmitter (RF TX) sends signals wirelessly to the RF receiver (RF RX) placed at the control section. This wireless communication ensures that alerts are delivered quickly over long distances without the need for wired connections.

The LCD display module, as shown in Fig. 2, is used to display real-time information such as detection status, alert messages, or warning notifications. When an animal or human is detected near the railway track, the system activates alert mechanisms such as buzzers or warning signals to notify railway authorities and prevent possible collisions.

Thus, the system architecture shown in Fig. 2 integrates sensing, processing, communication, and alert modules into a unified system that enables continuous monitoring, fast detection, and timely warning to improve railway safety and wildlife protection.

3. Working Methodology

3.1 The system initializes all hardware components, including sensors, camera modules, and communication devices.
3.2 Sensors continuously monitor the railway track area for any movement.
3.3 When motion is detected, the camera captures real-time images or video.
3.4 The captured data is processed using the YOLO-based DCNN model to identify whether the object is an animal or human.
3.5 If no relevant object is detected, the system continues monitoring.
3.6 If an animal or human is detected near the track, the system generates an alert.
3.7 The alert is transmitted to the train driver and control room through the communication module.
3.8 Simultaneously, the system activates the buzzer and sound repelling mechanism to drive the animal away safely.
3.9 The system continues monitoring until the track is cleared, after which it returns to normal operation.

4. Model Implementation

The object detection model is based on the YOLO architecture, which enables real-time detection with high speed and efficient performance. The model is trained on a dataset containing images of various animals and humans to ensure reliable classification. Transfer learning techniques are applied to improve detection performance and reduce training time. The trained model processes input images captured from the camera module and identifies the presence of animals or humans near the railway track.

4.1 Software Used

The proposed system uses several software tools for model development, training, and implementation. The YOLO object detection model is developed using the Python programming language, which supports machine learning and image processing applications. Deep learning frameworks such as TensorFlow or PyTorch are used to train and test the neural network model.
The OpenCV library is used for image processing tasks such as image capture, resizing, and object detection from live video streams. The trained model is executed on the Raspberry Pi system for real-time detection. Additionally, the Arduino IDE software is used to program the microcontroller for controlling sensors, communication modules, and alert devices.

4.2 Hardware Used

The hardware components play an important role in implementing the proposed system. The main hardware used includes Raspberry Pi, Arduino (or ESP32), camera module, IR/PIR sensors, RF transmitter and receiver, LCD display, and buzzer.
The Raspberry Pi acts as the main processing unit that runs the trained YOLO model and processes real-time image data. The Arduino or ESP32 controls sensor operations and manages communication between different components. The camera module captures live images from the railway track area, while IR/PIR sensors detect motion near the track.
The RF transmitter and receiver modules are used for wireless communication between system units. The LCD display shows alert messages and system status, and the buzzer provides warning signals when animals or humans are detected near the railway track.

Experimental Setup

The proposed wildlife detection system was implemented using a combination of hardware and software components, including Arduino, camera module, and wireless communication modules. The object detection model based on YOLO was trained and tested using a dataset consisting of various animal and human images under different environmental conditions such as daylight, nighttime, and partial occlusion.
The system was deployed in a simulated railway environment to evaluate its performance in real-time detection and alert generation.

Results

The system demonstrated high performance in detecting animals and humans near railway tracks. The YOLO-based model achieved an accuracy of 98.8% for animal detection and 99.8% for human detection, ensuring reliable identification under varying conditions.
The detection speed was fast enough to support real-time monitoring, allowing alerts to be generated within a very short time after detection. The integration of sensors further improved detection reliability by triggering the camera only when motion was detected, reducing unnecessary processing.
The alert system successfully transmitted warning signals through IoT/RF communication modules to the control unit and train system. Additionally, the alarm mechanism effectively responded by generating sound signals to repel animals from the track.

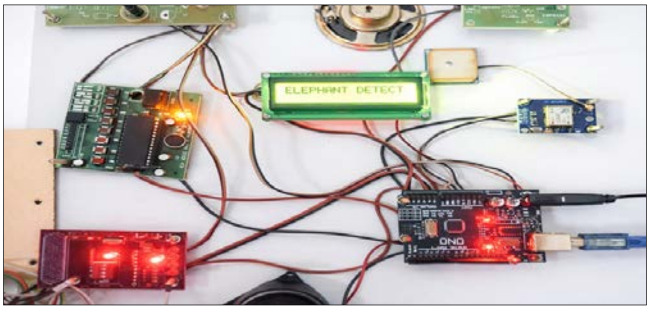

Fig 2: Animal name is displayed on LCD and divice emitting the noise.

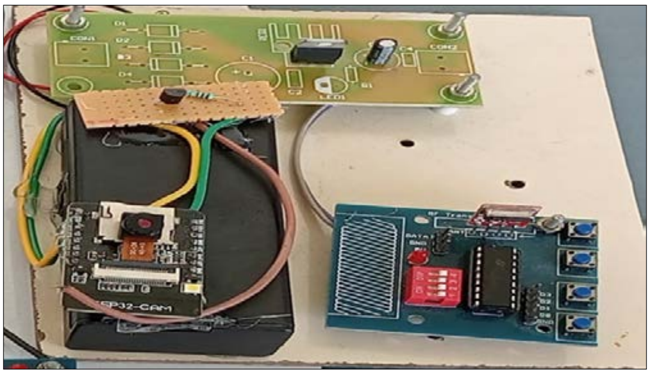

Fig 3: Input signal is given through the transmitter by manually.

Discussion

The results indicate that the proposed system is highly effective in addressing the limitations of existing wildlife detection methods. Unlike traditional approaches that focus only on detection, this system integrates real-time monitoring, alert generation, and preventive action, making it more practical for real-world deployment.

The high accuracy achieved by the YOLO model demonstrates the effectiveness of deep learning in identifying animals even under challenging environmental conditions. The use of embedded systems such as Arduino ensures low-cost implementation and easy deployment in remote areas.

However, certain challenges remain. The system performance may be affected by extreme weather conditions such as heavy rain or dense fog. Additionally, the accuracy depends on the quality and diversity of the training dataset. Future improvements can include the use of thermal imaging cameras and more advanced deep learning models to enhance detection reliability.

Overall, the proposed system provides a scalable, efficient, and intelligent solution for reducing wildlife–train collisions and improving railway safety.

Conclusion

This work presents an intelligent and automated wildlife detection and alert system designed to reduce wildlife–train collisions in railway tracks passing through forest and wildlife areas. The proposed system integrates computer vision, deep learning, and embedded systems to enable real-time monitoring and early detection of animals and humans near railway tracks.

The implementation of the YOLO-based object detection model demonstrated high accuracy and efficiency in identifying objects under various environmental conditions. The integration of sensors, communication modules, and alert mechanisms ensures timely notification to railway authorities and enables preventive action. Additionally, the inclusion of a sound-based repelling system enhances safety by guiding animals away from danger zones without causing harm.

Compared to existing methods, the proposed system provides a comprehensive solution by combining detection, alert generation, and preventive mechanisms in a single framework. This approach significantly improves reliability, reduces response time, and minimizes the risk of accidents.

Overall, the system contributes to both railway safety and wildlife conservation by providing a scalable, cost-effective, and efficient solution. It highlights the potential of artificial intelligence and IoT technologies in solving real-world environmental challenges and supporting sustainable infrastructure development.

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