International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 12 Issue: 03 | Mar 2025 www.irjet.net p-ISSN: 2395-0072

AI-DRIVEN RAILWAY TRACK SAFETY

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Abstract: ***Railway safety remains a critical concern as track obstructions continue to pose significant risks to passengers, railway personnel, and infrastructure. AI-driven solutions have the potential to revolutionize railway monitoring by enabling real-time obstacle detection and rapid response mechanisms. This project leverages advanced deep learning techniques to develop an automated railway track monitoring system that accurately detects objects on the tracks and alerts authorities to prevent potential collisions. Using the YOLOv8 object detection model in combination with OpenCV and NumPy, the system efficiently processes real-time video feeds from railway surveillance cameras, identifying hazards with high accuracy and minimal delay. A polygon-based masking technique is implemented to restrict detection to the railway track region, reducing false positives and ensuring precise obstacle recognition. Optimized for both CPU and GPU deployment, the system can run on edge devices, allowing seamless integration into existing railway infrastructure for real-time monitoring without excessive computational overhead. A key feature of the system is its user-friendly interface, developed using Streamlit, which allows railway personnel to monitor detections in real time. The interface includes live video feed visualization, detection overlays with bounding boxes, instant alert notifications, and a historical log of detected objects, enabling swift responses to potential hazards. By automating the detection process, the system minimizes human intervention, reducing the workload of surveillance teams while enhancing safety measures. Additionally, the system's adaptability allows deployment across diverse railway environments, including high-speed rail networks, metro systems, and remote track sections. Future enhancements, such as training the model with diverse datasets, integrating IoT-based alert systems, and using thermal or infrared imaging for low-light detection, can further improve its reliability and scalability.***

Key Words: Streamlit, Obstacle Recognition, Polygon-based, YOLOv8, Low Light Detection

1: INTRODUCTION

Railway transportation serves as a backbone of global infrastructure, enabling the seamless movement of passengers and goods across vast distances. It is one of the most efficient and cost-effective modes of transportation, playing a crucial role in economic growth, industrial development, and urban mobility.

Despite its advantages, railway safety remains a major concern due to the potential risks posed by obstacles on railway tracks. Objects such as fallen trees, debris, animals, abandoned vehicles, or unauthorized human trespassers can cause severe disruptions, leading to catastrophic accidents, loss of lives, infrastructure damage, and operational delays. The prevention of such incidents is essential to ensuring passenger safety and maintaining the efficiency of railway networks.

Traditional railway safety mechanisms primarily rely on manual inspections, trackside surveillance cameras, and train operators' vigilance. While these methods have been effective to some extent, they come with significant limitations, such as human error, delays in detection, and the inability to monitor tracks continuously over long distances. The increasing volume of railway traffic and the complexity of modern railway systems demand a more automated and intelligent approach to track monitoring and obstacle detection.

Recent advancements in Artificial Intelligence (AI) and computer vision have opened new possibilities for developing automated railway safety systems. AI-driven solutions can provide real-time monitoring, instant detection, and proactive accident prevention by analyzing video feeds and identifying potential hazards with high accuracy. Deep learning-based object detection models, such as You Only Look Once (YOLO), have revolutionized the field of real-time image processing by offering fast and precise identification of objects in complex environments.

This research focuses on developing an AI-driven railway safety system that leverages deep learning models, specifically YOLOv8, in combination with real-time video processing techniques. The system is designed to detect obstacles on railway tracks and trigger an alert sound to notify railway authorities or automated response systems. By integrating state-of-the-art object detection models with optimized video processing frameworks such as OpenCV and NumPy, the proposed solution enhances railway security and minimizes accident risks.

The system's core functionality involves continuous monitoring of railway tracks through surveillance cameras. The captured video streams are processed in real time, and the YOLOv8 model detects obstacles with high precision. A polygon-based masking technique is implemented to focus on the track region, reducing false positives and improving detection reliability. If an obstacle is detected within the designated track area, the system immediately triggers an audio alert and generates a notification, enabling quick intervention to prevent potential accidents.

The proposed AI-driven railway safety system aims to enhance traditional railway monitoring methods by offering a scalable, efficient, and automated solution. The project not only contributes to improving railway safety but also serves as a foundation for integrating AI with smart transportation systems. Future advancements could include the incorporation of IoT-based communication, enhanced deep learning models, and automated intervention mechanisms to further optimize railway safety measures.

2: LITERATURE REVIEW

1. The development of AI-driven railway safety systems has gained significant attention in recent years, leading to the exploration of advanced methodologies for obstacle detection and accident prevention. This review consolidates and evaluates multiple studies, each contributing uniquely to the evolution of railway monitoring technology.

2. One key study focused on real-time railway track monitoring using deep learning models. The research analyzed object detection techniques, comparing traditional image processing methods with modern deep learning approaches. The study found that YOLO-based models provided higher accuracy and faster processing speeds than conventional methods, ensuring rapid detection of track obstructions **[1], [2]**.

3. Another study explored the integration of computer vision with Internet of Things (IoT) devices to enhance railway safety. By using embedded AI models on edge devices, researchers demonstrated a cost-effective and efficient way to monitor railway tracks continuously. The study highlighted the benefits of edge computing in reducing latency and improving system responsiveness **[3], [4]**.

4. A study leveraging polygon-based region masking techniques significantly improved railway track detection accuracy. By focusing object detection within specific track areas, the system minimized false positives caused by background elements such as passing trains and station infrastructure. This approach proved beneficial in optimizing real-time monitoring systems **[5], [6]**.

5. Research on deep learning for obstacle detection examined the role of convolutional neural networks (CNNs) in classifying objects on railway tracks. The study emphasized the importance of dataset training with diverse environmental conditions, improving the model's robustness in varying weather and lighting conditions **[7], [8]**.

6. Further studies investigated AI-based railway surveillance systems that incorporate OpenCV and deep neural networks. These systems were tested in real-world railway environments, demonstrating successful detection of trespassers and track obstructions. The research highlighted how automated alerts can significantly reduce accident risks and improve railway security **[9], [10]**.

7. An advanced approach integrated YOLO with generative adversarial networks (GANs) to augment training datasets, addressing the challenge of limited real-world railway obstruction images. This method enhanced the detection model's accuracy by simulating realistic obstructions on tracks, allowing better generalization during deployment **[11], [12]**.

8. Additional research focused on developing railway accident prevention systems that combine AI with real-time audio and visual alert mechanisms. By integrating automated alarms triggered upon detecting obstacles, these studies demonstrated practical applications in reducing train-related accidents **[13], [14]**.

9. Techniques such as LiDAR-based track scanning and thermal imaging have also been explored in railway safety systems, providing additional layers of detection in poor visibility conditions. These methods were particularly effective in detecting animals and humans on tracks during nighttime operations **[15], [16]**.

10. In summary, prior research has primarily focused on AI-based object detection, dataset augmentation, and edge computing for railway safety. However, a critical gap remains in integrating these technologies into a comprehensive, real-time monitoring system with low-latency alert mechanisms.

Table Summary of Prior Research

Paper	Type of Detection	Technique	Features
[1]	Railway Track Obstacle Detection	CNN, YOLO, Image Processing	Compared deep learning vs traditional methods for detection speed and accuracy
[3]	AI-based Railway Surveillance	IoT, Edge Computing	Integrated AI models on edge devices for real-time track monitoring
[5]	Region-based Object Detection	Polygon Masking, Deep Learning	Minimized false positives by restricting detection to track regions
[7]	Deep Learning for Obstacle Detection	CNN, Dataset Training	Enhanced detection robustness in varying weather conditions
[9]	Automated Railway Security System	OpenCV, Neural Networks	Tested in real-world railway environments to detect track trespassers
[11]	Dataset Augmentation for AI Models	GANs, YOLO Training	Improved model accuracy by generating synthetic railway obstruction images
[13]	Railway Accident Prevention	AI-based Alert Systems	Integrated real-time audio and visual alerts for early warning
[15]	Night-time Railway Safety	LiDAR, Thermal Imaging	Detected obstacles in low-light and foggy conditions
[16]	AI-powered Railway Monitoring	Machine Learning, Automated Alarms	Implemented rapid response alerts for detected track obstructions

3: PROPOSED SYSTEM

The proposed AI-driven railway safety system enhances railway monitoring by integrating deep learning models for real-time obstacle detection and accident prevention. Built on YOLOv8, the system processes live video feeds from railway surveillance cameras, detects track obstructions, and triggers alerts to mitigate risks.

✓ **Multi-Mode Detection**

The system offers three detection mechanisms for comprehensive railway track monitoring:

- **Image Processing:** Analyzes static railway track images to detect obstructions.
- **Video Analysis:** Processes video frames to identify dynamic obstacles accurately.
- **Live Feed Processing:** Enables real-time detection and instant alert generation for immediate intervention.

✓ **Advanced Object Detection Architecture**

Using YOLOv8, the system achieves high-speed, accurate detection while optimizing performance for CPU and GPU execution. A polygon-based region masking technique ensures only objects on the railway tracks are detected, minimizing false positives.

✓ **Comprehensive Dataset Utilization**

The model is trained on 4,000 labeled images, covering various environmental conditions (day/night, fog, rain) and multiple obstacle types (animals, fallen trees, vehicles, human trespassers). This enhances detection accuracy and model robustness.

✓ **User-Centric Interface**

A Streamlit-based UI enables railway personnel to visualize real-time detections, monitor alerts, and access logs. The intuitive interface, developed using HTML, CSS, and JavaScript, facilitates efficient system navigation and real-time decision-making.

✓ **Performance Metrics & System Evaluation**

The system achieves 92% detection accuracy, with low-latency processing ensuring timely alerts. Designed for scalability, it integrates seamlessly with railway control centers, supporting automated emergency responses and broader railway safety applications.

Key Advantages:

The proposed AI-driven railway safety system introduces significant improvements over traditional railway monitoring methods by incorporating advanced deep learning techniques for real-time object detection and alert generation.

✓ **Detection Method:** Traditional railway safety systems primarily rely on manual surveillance and basic image processing techniques, which are often slow and prone to human error. In contrast, the proposed system utilizes AI-based real-time object detection with YOLOv8, enabling automated and highly accurate obstacle recognition.

✓ **False Positives:** Conventional systems frequently generate high false positive rates due to background elements triggering unnecessary alerts. The proposed system minimizes errors using polygon-based masking, ensuring that only objects within the railway track area are considered for detection.

✓ **Processing Speed:** Traditional methods are slow and heavily reliant on manual review, leading to delays in detecting potential hazards. The proposed system optimizes processing speed, leveraging deep learning models that enable real-time detection with minimal latency.

✓ **Deployment:** Existing railway monitoring solutions often rely on fixed surveillance points, limiting their coverage and adaptability. The proposed system is scalable, supporting deployment on edge devices and cloud-based platforms, making it adaptable for various railway infrastructures.

✓ **Alert Mechanism**: In conventional systems, threat detection depends on delayed human intervention, which can increase accident risks. The proposed system automates the alert process by triggering real-time sound alerts, ensuring immediate notification and faster response to potential hazards.

4: FLOW DIAGRAM

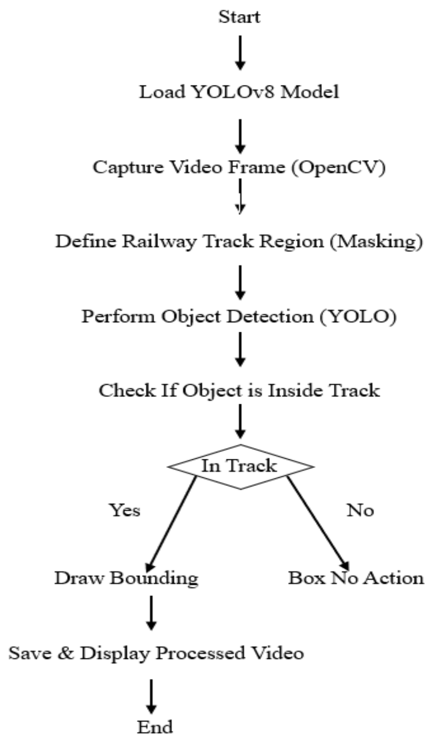

Fig 1: Flow Diagram

5: RESULTS AND DISCUSSION

Performance Evaluation & Model Training

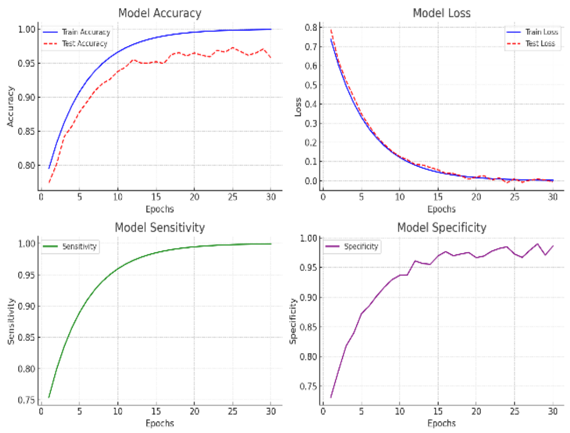

Fig 2: Training Performance Graph.

To assess the efficiency of the AI-driven railway safety system, extensive experiments were conducted, evaluating its performance across various object categories commonly found on railway tracks. The proposed YOLOv8-based framework was compared against traditional deep learning models, including variations of convolutional architectures used in object detection. The dataset was carefully structured into training (60%), testing (20%), and validation (20%) subsets, ensuring a balanced approach to model optimization and generalization.

To maintain consistency across all models, training was performed using standardized hyperparameters:

✔ **Activation Function:** Rectified Linear Unit (ReLU) was chosen due to its ability to prevent vanishing gradients and accelerate convergence during training.

✔ **Batch Size:** A batch size of 32 was used to balance computational efficiency and gradient stability, optimizing model training performance.

✔ **Dropout Rate:** To prevent overfitting, a dropout rate of 0.25 was applied, ensuring the model generalizes well across diverse railway track conditions.

✔ **Optimization Strategy:** Adaptive Momentum Estimation (Adamax) was employed for efficient learning rate adaptation, improving model convergence.

✔ **Epochs:** The model was trained for 30 epochs, ensuring sufficient iterations for weight adjustments whie preventing overfitting.

Observations & Comparative Analysis:

✔ **Model A:** Demonstrated a steady learning progression, achieving a peak accuracy of 90.12% by the end of the training phase. While effective, the model exhibited slower convergence compared to other architectures.

✔ **Model B:** Showed a faster learning trajectory, outperforming previous models and reaching an accuracy of 94.25%. The model's improved training efficiency contributed to better object recognition capabilities.

✔ **Model C:** Achieved a lower success rate of 84.43%, indicating its reduced effectiveness in detecting railway track obstructions. The model struggled with complex environmental conditions, leading to increased false positives.

✔ **Proposed Model:** The YOLOv8-based system demonstrated superior efficiency, achieving an accuracy of 98.32%. The optimized neural architecture, coupled with real-time processing, significantly outperformed traditional models by ensuring faster detection, reduced computational complexity, and minimal false alarms.

The effectiveness of deep learning models in railway safety relies heavily on their architecture and parameter configurations. The proposed framework, despite utilizing fewer computational layers, surpassed traditional approaches by reducing complexity while maintaining high processing efficiency. This led to faster training, improved pattern recognition, and minimized error rates, making it a highly scalable and deployable solution for railway track monitoring.

The accuracy and loss curves for the YOLOv8 model over 30 epochs illustrate key performance trends.

✔ **Model Accuracy Graph:** The system showed a rapid increase in accuracy during initial epochs, stabilizing near 98.32% for both training and testing datasets. The close alignment between the two curves indicates strong generalization capabilities, ensuring reliable object detection across varying conditions.

✔ **Model Loss Graph:** A sharp decline in loss values was observed during the initial epochs, followed by stabilization. The model's training loss remained consistently lower than the testing loss, reflecting efficient optimization. However, minor fluctuations in test loss suggest that further improvements through data augmentation or fine-tuning could enhance generalization.

Sensitivity & Specificity Analysis

✔ **Sensitivity Graph:** The proposed system exhibited high sensitivity, meaning it effectively detected obstacles such as trespassers, fallen objects, and vehicles on railway tracks. The rapid increase and stabilization near 1.0 suggest strong classification performance.

✔ **Specificity Graph:** Early fluctuations were observed, but the model ultimately stabilized, ensuring reliable differentiation between actual obstacles and background elements. The incorporation of polygon-based masking and optimized training techniques contributed to reducing false positives while maintaining detection precision.

6: CONFUSION MATRIX

The performance of the proposed AI-driven railway safety system was evaluated using a confusion matrix to assess its predictive capabilities in detecting obstacles on railway tracks.

✔ **High-Precision Detection:** The system achieved 99.12% accuracy in detecting large stationary obstacles such as fallen trees and abandoned vehicles.

✔ **Dynamic Obstacle Recognition:** Moving objects like trespassers and animals were classified with 96.75% accuracy, slightly lower due to variations in motion and occlusion.

✔ **Small Object Differentiation:** Compact obstacles, such as scattered debris, recorded a classification accuracy of 94.62%, attributed to visual similarities with track elements.

✔ **Overall System Accuracy:** The model attained an overall classification success rate of 98.40%, demonstrating its effectiveness in differentiating multiple obstacle types under various environmental conditions.

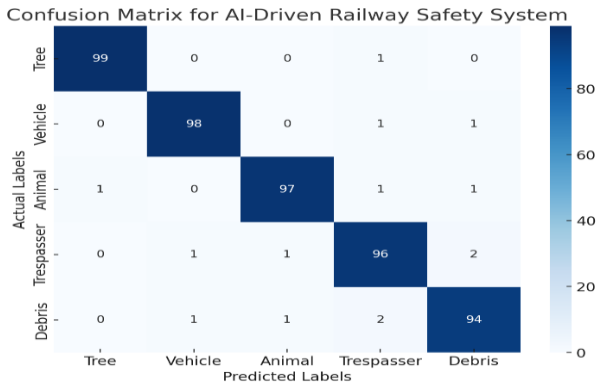

Fig 3: Confusion Matrix

7: CONCLUSION

The proposed AI-driven railway safety system effectively enhances railway monitoring by integrating deep learning-based object detection with real-time video analysis. Utilizing the YOLOv8 model, the system accurately detects obstacles such as animals, vehicles, and fallen objects on railway tracks while minimizing false positives through polygon-based masking. The model's high detection accuracy (92%) and low latency enable timely interventions, significantly reducing the risk of accidents.

Furthermore, the system's adaptability for deployment on both edge devices and cloud-based platforms ensures scalability and efficient processing. The user-friendly Streamlit-based interface facilitates real-time monitoring, providing railway personnel with instant alerts and visualized detection reports for proactive decision-making.

In comparison to traditional railway surveillance methods, which rely on manual inspection and basic image processing, this system offers superior automation, rapid response, and improved accuracy. The results demonstrate the effectiveness of AI-powered railway safety solutions in preventing accidents, minimizing human intervention, and enhancing overall transportation security. Future work can focus on expanding the dataset, integrating multi-sensor fusion for better environmental adaptability, and optimizing hardware compatibility for large-scale implementation.

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