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Real-Time AI-Powered Railway Track Surveillance System

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Abstract
One of the most popular and economically significant forms of transportation in the world is railroads. However, track impediments including trespassers, stray animals, fallen debris, landslides, and stalled cars at crossings continue to pose significant safety concerns for railway networks. Signaling systems and human monitoring by loco pilots, which are constrained by reaction times, visibility limitations, and environmental disruptions, are the main components of conventional railway safety methods.
This study suggests a Real-Time AI-Powered Railway Track Surveillance System that combines edge computing, computer vision, and deep learning to detect hazards in advance. The YOLO (You Only Look Once) object detection architecture, on which the system is based, allows for the quick and precise identification of track invasions. By concentrating just on the active track zone, a Region of Interest (ROI) masking technique is used to lower false positives. In high-speed train contexts, the suggested model improves situational awareness, lessens reliance on manual monitoring, and closes the detection-braking gap. The study shows how clever automation may lower the probability of accidents and greatly increase operational safety.

Keywords: Railway Safety, Deep Learning, Computer Vision, YOLO Framework, Real-Time Hazard Detection

1. Introduction

The foundation of both domestic and international transportation networks is made up of railway systems. Trains now travel at speeds of more than 100–300 km/h in several areas due to the growing demand for high-speed rail services. Although interlocking mechanisms, signaling protocols, and mechanical systems guarantee safe train-to-train travel, they do not address unforeseen external risks that may be present on the tracks.
Trains must brake across long distances on predetermined routes due to their mass and momentum. Even with emergency braking, a high-speed train may require several hundred meters to come to a complete stop. If an obstruction is found too late, a collision is unavoidable. This seriously jeopardizes the safety of modern rail operations.
CCTV cameras and sensor-based systems like infrared or ultrasonic sensors are examples of traditional surveillance techniques. Nevertheless, these systems are either incapable of classifying objects or are

passive (used only for post-incident analysis). An intelligent, real-time, automated surveillance system that can identify dangers before they cause accidents is therefore required.

By implementing computer vision and deep learning algorithms right at the edge, the suggested AI-powered railway track monitoring system solves this problem and permits proactive safety management.

2. Problem Statement

Hazard detection systems are still antiquated despite improvements in locomotive technology. Among the main obstacles are:

1. Detection-Braking Gap: For high-speed trains, human reaction time is inadequate.
2. Environmental Vulnerability: Visual acuity is diminished by fog, rain, and darkness.
3. Absence of Real-Time Autonomy: Present systems lack intelligence and are passive.

To overcome these constraints, an automated, AI-driven solution is needed.

3. Literature Review

Artificial intelligence is increasingly being used in transportation safety, according to recent studies. By enabling automated track inspection systems, Frej et al. (2026) highlighted the significance of machine learning in preventing railroad accidents. In their comparison of YOLOv11 and transfer learning models for railway fault detection, Rodríguez-Abreo et al. (2025) showed enhanced detection performance using optimized deep learning architectures. Yang et al. (2025) suggested employing YOLO models for foreign object recognition in UAV-based railway intrusion detection. Using deep learning models for real-time detection, Chang et al. (2025) created an integrated smart railway safety monitoring system. Machine learning-driven digital twin systems for predictive railway maintenance were presented by Sresakoolchai and Kaewunruen (2025).

According to these investigations, AI-based detection systems perform noticeably better than conventional sensor-based methods. Nevertheless, more organized implementation is still needed in the areas of edge computing integration, ROI-based spatial filtering, and real-time warning mechanisms.

4. Proposed Methodology

The steps of the suggested framework are as follows:

4.1 Capturing Images: Continuous video streams from locomotives or trackside infrastructure are captured by high-resolution cameras.

4.2 YOLO-Based Identification: A single-pass convolutional neural network is used to process each frame. Class probabilities and bounding boxes are produced concurrently.

4.3 Filtering by Region of Interest: To cut down on false alarms, a polygon-based ROI mask eliminates non-track items.

4.4 Logic of Risk Assessment: Train speed and closeness are taken into consideration while evaluating detected dangers.

4.5 Generation of Alerts: IoT communication is used to provide tiered alerts to control rooms and loco pilots.

5. Impact of Deep Learning in Railway Safety

Deep learning increases classification accuracy and does away with the need for human feature engineering. The YOLO architecture is appropriate for high-speed settings since it can handle 45–150 frames per second.

By using data augmentation techniques including brightness variation, contrast modulation, and rotation, the system maintains detection consistency under different lighting situations. In practical situations, this robustness guarantees dependable performance.

6. Unified Workflow Architecture

Figure 1: Unified Workflow Architecture of the Proposed System

• Constant video recording • Inference processing in real time • Filtering in space • Miti-level automated alerts.

The integrated workflow incorporates:

- Constant video recording
- Inference processing in real time
- Filtering in space
- Risk assessment
- Multi-level automated alerts

The method improves operating efficiency and lowers the likelihood of accidents by reducing latency between detection and intervention.

7. Applications in Railway Operations

Beyond just identifying hazards, the suggested AI system facilitates:

1. proactive tracking
2. Predictive upkeep
3. Intelligent traffic control
4. Security of smart stations
5. Readiness for autonomous train operations (GoA4)

8. Future Scope

Future enhancements include:

- Digital Twin integration
- Multi-sensor fusion (LiDAR + Thermal Imaging)
- 6G-enabled distributed railway intelligence
- Fully autonomous train systems

9. Conclusion

The suggested Real-Time AI-Powered Railway Track Surveillance System offers a clever and proactive answer to contemporary railroad safety issues. The approach improves situational awareness and closes the detection-braking gap by combining YOLO-based deep learning, edge computing, and ROI-based spatialfiltering.

An important step toward lowering collision risks, enhancing operational dependability, and guaranteeing passenger safety is the shift to intelligent railway infrastructure. The study comes to the conclusion that AI-driven surveillance is essential for the future of high-speed rail transportation, not just an improvement.

10. References

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