

Enhancing Railway Accident Prevention Using Deep Learning, Machine Learning, and GPS Tracking: A Historical and Knowledge-Based Analysis

Vikas Chandra Giri¹, Ms. Parineeta Jha²

Student, Computer Science & Engineering, RSR-Rungta College of Engineering and Technology, Bhilai, India¹

Assistant Professor, Computer Science & Engineering, RSR-Rungta College of Engineering and Technology, Bhilai, India²

Abstract: Railway accidents pose risks to passenger safety, infrastructure, and economic stability. Traditional accident prevention methods rely on rule-based systems and human intervention, often failing to address real-time risks effectively. This paper integrates Deep Learning (DL), Machine Learning (ML), and Global Positioning System (GPS) tracking to enhance railway accident prevention. By leveraging historical accident data and knowledge-based analysis, we propose an intelligent system capable of real-time anomaly detection, predictive maintenance, and automated decision-making.

Keywords: Artificial Intelligence, Data Processing, Deep Learning, GPS, Machine Learning

I. INTRODUCTION

Railway transportation is one of the most widely used modes of travel and freight movement globally. However, railway accidents continue to pose challenges due to derailments, track failures, signal errors, and human negligence. Traditional railway safety mechanisms primarily depend on manual inspections and reactive responses, which often fail to prevent accidents before they occur. The integration of artificial intelligence (AI), specifically DL and ML, along with GPS tracking, presents a proactive approach to accident prevention by predicting and mitigating risks in real time.

II. LITERATURE REVIEW

Prior research explored rule-based automation, sensor monitoring, and human intervention:

- In 2017, Anusuya Patil proposed a crack detection system.
- In 2020, Habib Hadj-Mabrouk utilized ML for accident prediction.
- In 2021, Zhihan Wang developed an AI-based accident analysis system.
- In 2022, Zhipeng Zhang introduced a DL tool for trespassing detection.

III. METHODOLOGY

The proposed methodology consists of the following key components:

- A. Historical Data Analysis: Examining past railway accidents to identify patterns and common causes.
- B. Machine Learning Models: Developing and training ML models on historical data to predict accident risks.
- C. Deep Learning Techniques: Utilizing DL for image recognition, anomaly detection, and real-time safety monitoring.
- D. GPS-Based Monitoring: Implementing GPS tracking to monitor train positions, prevent collisions, and optimize routes.

IV. IMPLEMENTATION AND RESULTS

The implementation involves collecting railway accident datasets, training ML/DL models, and integrating GPS tracking systems. The study evaluates:

- The accuracy of ML algorithms in predicting railway failures.



- The effectiveness of DL models in detecting safety anomalies.
- The reliability of GPS tracking in real-time train monitoring and accident prevention.

A model-based DL approach enhances anomaly detection capabilities, making railway operations more secure and efficient.

V. DISCUSSION AND FUTURE WORK

While AI and GPS technologies show promise in railway accident prevention, challenges remain in terms of:

- Data Availability – Limited access to real-time railway datasets.
- Model Accuracy – Need for continuous model refinement to improve prediction capabilities.
- Centralized Database – Essential for integrating multiple AI models across railway networks.

Future research will focus on refining ML/DL models, integrating sensors and high-resolution cameras, and testing the system in real-world railway environments to ensure reliability and effectiveness.

VI. CONCLUSION

The integration of DL, ML, and GPS tracking offers a promising approach to railway accident prevention. By leveraging historical data, predictive analytics, and real-time monitoring, the proposed framework enhances railway safety, reduces accident risks, and optimizes operational efficiency. The findings underscore the importance of AI-driven solutions in modernizing railway safety mechanisms and paving the way for safer and more efficient railway networks.

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