

A Comprehensive Review of Intelligent Railway Track Monitoring and Safety Systems Using IoT, Sensors, and Machine Learning

Suprio Dutta¹, Rajosi Dey², Swastika Roy³, Aritra Ghosh⁴, Soumyadip Ghosh⁵,
Pradip Mandal⁶, Prasun Chowdhury⁷

^{1,2,3,4,5,6,7}Department of ECE, St. Thomas' College of Engineering & Technology, Kolkata, India 700023

ABSTRACT

Railway transportation remains one of the most critical modes of mass transit for passengers and freight worldwide. With the continuous expansion of railway networks and increasing operational speeds, ensuring track integrity and operational safety has become a major engineering and management challenge. Traditional railway inspection methods, such as manual patrols and dedicated inspection vehicles, though reliable, are limited by high operational costs, low inspection frequency, and lack of real-time monitoring capability. In recent years, rapid advancements in sensing technologies, Internet of Things (IoT), embedded systems, wireless communication, and artificial intelligence have transformed railway track monitoring and safety management. This review paper presents a comprehensive and systematic survey of intelligent railway track monitoring and safety systems, focusing on sensor-based approaches, IoT-enabled architectures, machine learning and deep learning techniques, and integrated safety frameworks. Key technologies such as accelerometer-based vibration analysis, vision-based crack detection, ultrasonic and infrared sensing, GPS/GSM-enabled alert systems, and predictive maintenance using unsupervised and supervised learning are critically reviewed. Furthermore, cybersecurity issues, system scalability, deployment challenges, and future research directions are discussed. By synthesizing recent research contributions, this review aims to provide researchers, practitioners, and policymakers with a consolidated understanding of current trends and emerging opportunities in intelligent railway safety systems.

Keywords: Railway safety, track monitoring, IoT, predictive maintenance, anomaly detection, machine learning, sensors, intelligent transportation systems

INTRODUCTION

Railway networks play a vital role in the socio-economic development of nations by enabling efficient and cost-effective transportation of passengers and goods. Owing to their high capacity, energy efficiency, and reliability, railways are considered a backbone of national transportation infrastructure. However, railway safety remains a persistent concern, particularly in developing countries with vast rail networks and aging infrastructure. Track-related failures such as cracks, misalignment, corrugation, and structural degradation are among the leading causes of derailments and accidents, resulting in loss of human life and economic damage [1].

Conventional railway track inspection techniques rely on scheduled manual inspections or specialized inspection vehicles equipped with high-precision instruments. Although these approaches provide accurate measurements and comply with safety regulations, they suffer from inherent limitations, including high cost, limited inspection frequency, dependency on human expertise, and inability to provide continuous real-time monitoring [2]. As railway operations move toward higher speeds and increased traffic density, these limitations necessitate the adoption of intelligent, automated, and data-driven monitoring solutions.

The emergence of Industry 4.0 has significantly influenced railway engineering, introducing advanced sensing technologies, IoT-based data acquisition, cloud computing, and artificial intelligence into railway monitoring systems [3]. Sensor-equipped in-service trains, low-cost embedded platforms, and wireless communication technologies now enable

continuous condition monitoring without disrupting regular operations. These developments have paved the way for predictive maintenance strategies, where potential faults are identified at an early stage, allowing proactive intervention before catastrophic failures occur [4].

This review focuses on intelligent railway track monitoring and safety systems developed over the last decade, with emphasis on sensor technologies, IoT architectures, machine learning-based anomaly detection, and integrated safety frameworks. Unlike traditional surveys that concentrate on a single technique, this paper provides a holistic perspective by covering diverse approaches and highlighting their comparative strengths, limitations, and application scenarios.

2. Evolution of Railway Track Monitoring and Safety Systems

The evolution of railway track monitoring systems can be broadly categorized into three phases: conventional inspection-based systems, sensor-assisted automated systems, and intelligent data-driven systems.

2.1 Conventional Inspection-Based Systems

Historically, railway safety relied on manual inspections conducted by trained personnel who visually examined tracks for defects. Dedicated track recording cars and ultrasonic testing vehicles were later introduced to improve inspection accuracy [5]. While these systems provide high-quality measurements, they are expensive to operate and are typically deployed at long intervals, leaving gaps in safety coverage.

2.2 Sensor-Assisted Automated Monitoring

With advancements in electronics and embedded systems, sensors such as accelerometers, strain gauges, ultrasonic sensors, infrared sensors, and temperature sensors began to be integrated into railway monitoring solutions. These sensors enabled automated detection of specific defects, such as cracks, vibrations, and environmental anomalies, with reduced human intervention [6]. The integration of GPS and GSM modules further enabled real-time fault localization and alert dissemination [7].

2.3 Intelligent Data-Driven Monitoring

The latest phase in railway safety evolution is characterized by the adoption of IoT, cloud computing, and artificial intelligence. In this paradigm, large volumes of sensor data are continuously collected, transmitted, and analyzed using machine learning algorithms to detect anomalies and predict future failures [8]. These systems shift maintenance strategies from reactive or preventive to predictive, significantly improving safety and cost efficiency.

3. Sensor Technologies for Railway Track Monitoring

Sensors form the foundation of intelligent railway monitoring systems. Different sensor modalities are employed depending on the type of defect, operational constraints, and environmental conditions.

3.1 Accelerometer-Based Vibration Monitoring

Accelerometers mounted on axle boxes or bogies capture vibrations generated due to wheel–rail interaction. Abnormal vibration patterns indicate track irregularities such as corrugation, misalignment, and impact defects [9]. Studies have shown that micromechanical accelerometers installed close to the wheel–rail contact point provide higher sensitivity to short and impact irregularities while enabling continuous monitoring using in-service trains [10]. Signal processing techniques such as time-domain statistics, frequency-domain analysis, and time–frequency representations are commonly applied to extract fault-related features.

3.2 Ultrasonic and Infrared Sensors

Ultrasonic sensors are widely used for detecting internal and surface cracks in rails by analyzing reflected acoustic waves. Infrared sensors are commonly employed in low-cost crack detection systems and obstacle detection robots [11]. These sensors are particularly effective for continuous inspection under varying lighting conditions and can operate during both day and night. However, ultrasonic systems may suffer from attenuation and coupling issues, requiring careful calibration.

3.3 Vision-Based Sensors

Camera-based systems combined with image processing and deep learning algorithms have gained significant attention for railway track inspection. Vision systems can detect surface cracks, foreign objects, and intrusions with high accuracy when integrated with convolutional neural networks and real-time processing units [12]. Despite their advantages, vision-based systems are sensitive to environmental variations such as illumination, weather, and occlusions, which may affect robustness in large-scale deployments.

4. IoT Architectures and Communication Frameworks for Railway Track Monitoring

The integration of Internet of Things (IoT) technologies has enabled scalable, real-time, and distributed railway monitoring systems [3][4]. IoT-based architectures facilitate continuous data acquisition from heterogeneous sensors, reliable communication, and intelligent decision-making [7].

4.1 IoT System Architecture

A typical IoT-enabled railway monitoring system follows a multi-layer architecture consisting of sensing, communication, processing, and application layers. The sensing layer comprises embedded sensors such as accelerometers, ultrasonic sensors, cameras, and environmental sensors deployed on tracks or rolling stock. The communication layer enables data transmission using wired or wireless technologies. The processing layer performs data aggregation, analytics, and anomaly detection using edge, fog, or cloud computing platforms. Finally, the application layer provides visualization, alerts, and maintenance decision support to railway operators [13].

4.2 Communication Technologies

Reliable communication is essential for real-time railway safety systems. Technologies such as GSM, GPS, ZigBee, Wi-Fi, and LoRa are commonly used for transmitting sensor data and alerts [14]. GSM and GPS modules enable real-time fault localization and messaging, while low-power wide-area networks like LoRa provide long-range communication with minimal energy consumption. The selection of communication protocols depends on coverage requirements, latency constraints, and deployment costs.

4.3 Edge and Cloud Computing Integration

Recent IoT architectures increasingly incorporate edge and cloud computing to handle large volumes of sensor data. Edge computing enables preliminary data processing and anomaly detection close to the data source, reducing latency and bandwidth usage. Cloud platforms provide scalable storage and advanced analytics for long-term trend analysis and predictive maintenance [15]. The hybrid edge–cloud approach improves system responsiveness while supporting data-driven maintenance planning.

4.4 Challenges in IoT-Based Railway Monitoring

Despite their advantages, IoT-based railway systems face challenges related to interoperability, data security, network reliability, and scalability. Harsh environmental conditions, electromagnetic interference, and mobility constraints further complicate deployment. Addressing these challenges requires standardized protocols, robust cybersecurity mechanisms, and resilient network design.

5. Machine Learning and Deep Learning Approaches for Railway Track Anomaly Detection

The growing availability of large-scale sensor data and advances in computational intelligence have led to widespread adoption of machine learning (ML) and deep learning (DL) techniques in railway track monitoring. These approaches enable automated detection of defects, anomaly identification, and predictive maintenance without excessive reliance on manual inspection [1][8].

5.1 Role of Machine Learning in Railway Track Monitoring

Machine learning techniques are primarily employed to learn patterns associated with normal track conditions and identify deviations that indicate potential faults. Depending on data availability and application requirements, ML methods can be broadly classified into supervised, unsupervised, and semi-supervised approaches. Supervised learning models require labeled datasets representing different fault types, whereas unsupervised techniques rely on intrinsic data structures to identify anomalies. In railway applications, the scarcity of labeled fault data has motivated increased interest in unsupervised and semi-supervised learning methods [1] [13].

5.2 Supervised Learning Techniques

Supervised learning approaches such as support vector machines, decision trees, random forests, and artificial neural networks have been used to classify track conditions based on extracted features from sensor signals. These models are capable of achieving high classification accuracy when trained on sufficiently large and well-annotated datasets. However, their effectiveness is constrained by the difficulty of obtaining labeled data across diverse track conditions, rolling stock types, and operational environments. Additionally, supervised models may struggle to generalize to unseen fault patterns, limiting their robustness in real-world deployments [12].

5.3 Unsupervised and Clustering-Based Anomaly Detection

Unsupervised learning techniques are particularly suitable for railway track monitoring, as they do not require labeled datasets. Clustering algorithms such as K-means, Gaussian mixture models, and density-based spatial clustering have been

widely investigated for identifying anomalous track segments. These methods group data based on similarity measures, allowing deviations from normal clusters to be interpreted as potential defects. Dimensionality reduction techniques, including principal component analysis, are often employed to improve clustering performance when dealing with high-dimensional sensor data [1][9].

Hybrid approaches that combine clustering with spectral or statistical analysis have demonstrated improved sensitivity to subtle track irregularities. By analyzing vibration or acceleration signals in the frequency domain and identifying deviations from baseline patterns, these methods enhance anomaly detection capability while maintaining computational efficiency [10].

5.4 Deep Learning-Based Approaches

Deep learning models have gained significant attention due to their ability to automatically learn hierarchical features from raw data. Convolutional neural networks are extensively used in vision-based railway inspection systems for detecting surface cracks, obstacles, and intrusions. When applied to time–frequency representations such as spectrograms, convolutional networks can also be used for vibration-based fault detection [12].

Recurrent neural networks and long short-term memory architectures have been explored for modeling temporal dependencies in sequential sensor data. These models are particularly effective for capturing long-term degradation trends and predicting future track conditions. Despite their high performance, deep learning approaches require substantial computational resources and large training datasets, which may limit their deployment on resource-constrained edge devices [1].

5.5 Hybrid and Ensemble Learning Models

To overcome the limitations of individual learning paradigms, recent research has focused on hybrid and ensemble learning frameworks. Hybrid models integrate signal processing techniques, such as spectral analysis, with machine learning algorithms to improve robustness and interpretability. Ensemble methods combine multiple classifiers to enhance detection accuracy and reduce false alarms. These approaches are well-suited for complex railway environments where fault signatures vary across locations and operating conditions [1][13].

5.6 Challenges and Considerations

Although machine learning and deep learning approaches offer significant advantages, several challenges remain. These include data imbalance, model interpretability, computational complexity, and real-time deployment constraints. Ensuring reliable performance across different railway networks requires robust model validation, adaptive learning strategies, and integration with domain knowledge. Addressing these challenges is essential for translating research advancements into practical railway safety solutions [8][15].

6. Integrated Railway Safety and Alert Systems

Beyond track condition monitoring, intelligent railway systems increasingly emphasize integrated safety and alert mechanisms that enable rapid response to hazardous situations. These systems combine sensing, communication, analytics, and actuation to prevent accidents, reduce response time, and enhance overall operational reliability [3][6].

6.1 Real-Time Alert and Notification Mechanisms

Real-time alert systems form a critical component of modern railway safety frameworks. Sensor-detected anomalies such as track cracks, excessive vibrations, obstacles, fire, or unauthorized intrusions are immediately communicated to operators through visual, auditory, or digital notifications. Technologies such as GSM and cellular data networks are commonly used to transmit alerts containing fault type, severity, and geographic location to control centers and maintenance teams. The availability of precise, real-time alerts enables timely intervention and minimizes the risk of catastrophic failures [5][6].

6.2 Smart Alert Systems Near Railway Tracks

Smart alert systems deployed near railway tracks focus on enhancing safety for both train operations and surrounding environments. These systems often integrate vision sensors, proximity sensors, and embedded controllers to detect humans, animals, or vehicles encroaching on tracks. Upon detection, alerts are issued locally through buzzers, lights, or display units, and remotely via wireless communication channels. Advanced implementations incorporate dynamic train speed control or automatic braking to mitigate collision risks, thereby reducing dependence on human reaction time [6][4].

6.3 Collision Prevention and Anti-Hijacking Frameworks

Collision prevention systems aim to detect and mitigate scenarios involving potential train-to-train or train-to-obstacle collisions. Integrated frameworks may utilize multiple sensing modalities along with authentication mechanisms to ensure

safe train operation. Anti-hijacking measures, including access control and operator authentication, further strengthen system security by preventing unauthorized train operation. When combined with real-time communication and centralized monitoring platforms, these frameworks contribute to a holistic railway safety ecosystem [3][7].

6.4 Integration with IoT and Intelligent Monitoring Platforms

Integrated safety systems increasingly leverage IoT platforms to unify monitoring, alerting, and control functions. Data from distributed sensors are aggregated and processed in real time, enabling coordinated decision-making across multiple system components. IoT dashboards provide operators with comprehensive situational awareness, including track health status, environmental conditions, and active alerts. The integration of safety systems with predictive maintenance analytics allows alerts to be contextualized within broader asset health assessments, supporting informed operational decisions [7][13].

6.5 System Reliability and Human–Machine Interaction

Reliability and usability are essential considerations in integrated safety system design. Redundancy in sensing and communication ensures continued operation under component failures or adverse conditions. Equally important is effective human–machine interaction, as operators must be able to interpret alerts quickly and accurately. Intuitive interfaces, prioritized alert presentation, and decision-support tools enhance operator effectiveness and reduce the likelihood of human error during critical situations [15].

6.6 Limitations and Deployment Challenges

Despite their benefits, integrated railway safety and alert systems face challenges related to system complexity, interoperability, and maintenance. Ensuring compatibility among heterogeneous devices and communication protocols can be difficult, particularly in legacy railway infrastructures. Additionally, false alarms and alert fatigue may reduce system effectiveness if not properly managed. Addressing these challenges requires careful system design, standardized interfaces, and adaptive alerting strategies [8][15].

7. Cybersecurity, Data Integrity, and System Reliability in Intelligent Railway Systems

As railway infrastructures increasingly adopt IoT, cloud computing, and artificial intelligence, cybersecurity and system reliability have emerged as critical concerns. Intelligent railway monitoring and safety systems rely on continuous data exchange between distributed sensors, communication networks, and centralized processing platforms, making them vulnerable to cyber threats, data corruption, and system failures[8][15].

7.1 Cybersecurity Threats in Intelligent Railway Systems

Cybersecurity threats in railway systems include unauthorized access, data manipulation, denial-of-service attacks, spoofing, and malware intrusion. Wireless communication channels and interconnected IoT devices expand the attack surface, potentially allowing adversaries to disrupt monitoring services or inject false data. Such attacks can compromise safety-critical decisions, leading to delayed maintenance actions or false alerts. Ensuring secure communication and access control is therefore essential for maintaining system trustworthiness [8].

7.2 Data Integrity and Authentication Mechanisms

Maintaining data integrity is vital for reliable anomaly detection and predictive maintenance. Authentication mechanisms ensure that data originates from legitimate sensors and authorized users, preventing spoofing and tampering. Techniques such as cryptographic hashing, secure key management, and mutual authentication protocols are commonly employed to protect data streams. Time synchronization and secure logging further enhance the traceability and accountability of system operations [15].

7.3 Secure Communication Protocols

Secure communication protocols play a fundamental role in protecting data transmitted over railway networks. Encryption techniques safeguard data confidentiality, while integrity checks detect unauthorized modifications. Lightweight security protocols are particularly important for resource-constrained IoT devices deployed in railway environments. Balancing security strength with computational efficiency remains a key design consideration [8][14].

7.4 Reliability and Fault Tolerance

Reliability is a core requirement for railway safety systems, as failures can have severe consequences. Fault-tolerant system design incorporates redundancy in sensors, communication links, and processing units to ensure continued operation under adverse conditions. Self-diagnostic and health-monitoring functions enable early detection of component degradation, supporting proactive maintenance and reducing downtime [15].

7.5 Resilience Against Data Loss and System Failures

Intelligent railway systems must be resilient to data loss caused by network disruptions, hardware failures, or environmental factors. Local data buffering, edge processing, and failover mechanisms help maintain functionality during connectivity outages. Cloud-based backup and recovery strategies further enhance system resilience by preserving historical data and analytical models [13][15].

7.6 Challenges and Research Directions

Despite ongoing advancements, cybersecurity and reliability challenges remain significant. The integration of legacy railway infrastructure with modern digital technologies complicates security management. Standardized security frameworks, continuous vulnerability assessment, and adaptive defense mechanisms are needed to address evolving threats. Future research should focus on developing railway-specific cybersecurity standards, intrusion detection systems tailored to railway networks, and robust architectures that ensure both safety and security [8][15].

8. Comparative Analysis and Discussion

This section provides a comparative analysis of the major approaches used in intelligent railway track monitoring and safety systems, highlighting their relative advantages, limitations, and suitability for real-world deployment. By synthesizing findings from the reviewed literature, this discussion aims to identify dominant trends and practical trade-offs that influence system design and adoption [1][4][9].

8.1 Comparison of Sensing Modalities

Different sensing technologies exhibit distinct strengths depending on the type of defect and operational context. Accelerometer-based systems are highly effective for continuous monitoring of track irregularities using in-service trains and offer good scalability at relatively low cost. Ultrasonic and infrared sensors provide reliable crack detection, particularly for surface and subsurface defects, but often require dedicated inspection platforms or close proximity to the track. Vision-based systems deliver rich spatial information and high detection accuracy for surface defects and obstacles; however, their performance is sensitive to environmental conditions and typically demands higher computational resources [12].

8.2 IoT-Enabled Systems versus Traditional Inspection Methods

Compared with traditional manual inspections and dedicated measurement vehicles, IoT-enabled monitoring systems offer significant advantages in terms of inspection frequency, real-time capability, and operational cost. Continuous data collection enables early fault detection and supports predictive maintenance strategies. Nevertheless, traditional methods remain valuable for calibration, validation, and compliance with regulatory standards. In practice, hybrid approaches that integrate IoT-based monitoring with periodic conventional inspections are emerging as the most effective solution [4][7].

8.3 Machine Learning and Deep Learning Performance Considerations

Machine learning approaches enhance the automation and intelligence of railway monitoring systems by enabling anomaly detection and fault classification. Unsupervised learning techniques are particularly attractive due to their reduced dependence on labeled data, while supervised and deep learning models often achieve higher accuracy when sufficient training data are available. However, deep learning methods typically involve higher computational complexity and reduced interpretability, which may limit their acceptance in safety-critical applications. The selection of learning models therefore depends on data availability, computational constraints, and regulatory requirements [12].

8.4 Integrated Safety Systems and Operational Impact

Integrated safety and alert systems demonstrate substantial benefits by linking monitoring, communication, and actuation components into a unified framework. Such systems improve response time, reduce reliance on human intervention, and enhance situational awareness. The effectiveness of integrated solutions is closely tied to system reliability, user interface design, and interoperability among heterogeneous components. Poorly managed integration can increase system complexity and maintenance burden [6][7].

8.5 Scalability, Cost, and Deployment Challenges

Scalability and cost remain key factors influencing large-scale adoption. Low-cost sensors and wireless communication technologies facilitate widespread deployment, but long-term maintenance, data management, and cybersecurity requirements can increase total system cost. Deployment in existing railway infrastructure poses additional challenges due to legacy systems, harsh environmental conditions, and varying operational practices across regions [8][15].

8.6 Summary of Comparative Insights

Overall, no single technology provides a complete solution for railway track monitoring and safety. Sensor-based IoT systems, combined with machine learning analytics and integrated alert mechanisms, offer the most promising pathway toward intelligent and resilient railway infrastructure. The comparative analysis underscores the importance of system-level design that balances accuracy, reliability, cost, and operational practicality [1][4].

9. Open Challenges and Future Research Directions

Despite significant progress in intelligent railway track monitoring and safety systems, several open challenges remain that hinder large-scale adoption and long-term sustainability. Addressing these challenges is essential to fully realize the benefits of IoT- and AI-driven railway infrastructure management [13][15].

9.1 Data Quality, Availability, and Standardization

One of the primary challenges in railway monitoring research is the availability of high-quality, representative datasets. Sensor data are often noisy, incomplete, and heterogeneous due to varying sensor types, installation locations, and operating conditions. Moreover, the lack of standardized data formats and labeling conventions limits data sharing and cross-network model generalization. Future research should focus on developing standardized data collection protocols, open benchmark datasets, and interoperable data models tailored to railway applications [13].

9.2 Scalability and System Integration

Scalability remains a critical concern for nationwide or transnational railway networks. While pilot deployments demonstrate feasibility, integrating thousands of sensors and communication nodes into existing infrastructure poses technical and organizational challenges. Legacy systems, proprietary interfaces, and fragmented management structures complicate system integration. Research efforts should explore modular architectures, standardized interfaces, and middleware solutions that facilitate seamless integration and incremental deployment [7][15].

9.3 Real-Time Processing and Edge Intelligence

Many intelligent monitoring approaches rely on cloud-based analytics, which may introduce latency and dependency on network connectivity. Real-time safety applications demand low-latency processing and high availability, motivating increased use of edge intelligence. Future work should investigate lightweight machine learning models, adaptive edge-cloud collaboration strategies, and efficient resource management to support real-time decision-making under constrained conditions [13][15].

9.4 Model Robustness, Interpretability, and Trust

The adoption of machine learning and deep learning models in safety-critical railway systems requires high levels of trust and transparency. Black-box models with limited interpretability may face resistance from operators and regulators. Ensuring robustness across diverse operational scenarios and providing explainable outputs remain open challenges. Future research should emphasize explainable artificial intelligence techniques, uncertainty quantification, and human-in-the-loop learning frameworks to enhance trust and acceptance [1][8].

9.5 Cybersecurity and Privacy Considerations

As railway systems become increasingly connected, cybersecurity threats and data privacy concerns grow in importance. Protecting distributed IoT devices and communication networks against evolving cyber attacks requires continuous monitoring and adaptive defense mechanisms. Research is needed to develop railway-specific cybersecurity frameworks, intrusion detection systems, and secure-by-design architectures that balance protection with performance [8][15].

9.6 Emerging Technologies and Future Trends

Emerging technologies offer new opportunities for advancing railway monitoring and safety. Digital twins can provide virtual representations of railway assets, enabling simulation-based analysis and predictive maintenance. Federated learning approaches may facilitate collaborative model training across multiple railway operators without sharing sensitive data. Autonomous inspection platforms, including drones and robotic vehicles, can complement sensor-based monitoring by providing flexible and targeted inspection capabilities. Exploring these technologies in realistic railway contexts represents a promising direction for future research [13][15].

CONCLUSION

This review has presented a comprehensive and structured overview of intelligent railway track monitoring and safety systems, emphasizing the convergence of sensing technologies, Internet of Things architectures, and machine learning-based analytics. Traditional inspection approaches, while reliable, are increasingly complemented by data-driven solutions

capable of continuous monitoring, real-time alerting, and predictive maintenance. The survey highlighted the evolution from manual and vehicle-based inspections to sensor-equipped in-service trains and integrated cyber-physical systems. A wide range of sensing modalities, including accelerometers, ultrasonic and infrared sensors, and vision-based systems, were reviewed and comparatively analyzed. Each modality offers distinct advantages and limitations, underscoring the importance of hybrid sensing strategies tailored to specific operational contexts. IoT-enabled architectures and edge-cloud integration were shown to play a critical role in enabling scalable, low-latency monitoring and decision support across large railway networks.

Machine learning and deep learning techniques have significantly advanced automated anomaly detection and fault diagnosis, with unsupervised and hybrid approaches addressing challenges related to limited labeled data and evolving fault patterns. Integrated safety and alert systems further enhance operational resilience by linking monitoring, communication, and actuation components into unified frameworks. At the same time, cybersecurity, data integrity, and system reliability were identified as essential enablers for trustworthy deployment in safety-critical environments.

The comparative analysis and discussion revealed that no single technology can comprehensively address all railway safety requirements. Instead, system-level integration that balances accuracy, interpretability, scalability, and cost is essential. Open challenges related to data standardization, scalability, real-time processing, model trustworthiness, and cybersecurity remain active research areas.

Overall, intelligent railway track monitoring represents a key pillar of modern intelligent transportation systems. Continued interdisciplinary research, standardization efforts, and collaboration between academia, industry, and railway operators will be vital for translating research innovations into robust, deployable solutions that enhance safety, reliability, and sustainability of railway infrastructure.

REFERENCES

- [1]. J. Pineda-Jaramillo, F. Bigi, I. Villalba-Sanchis, and P. Salvador-Zuriaga, "Anomaly detection in railway tracks using hybrid clustering and spectral analysis for predictive maintenance," *IEEE Access*, vol. 13, pp. 164265–164287, 2025.
- [2]. A. Bolshakova, D. Larionov, A. Boronachin, L. Podgornaya, R. Shalymov, E. Bokhman, and A. Tkachenko, "Specific features of using micromechanical accelerometers for monitoring short and impact irregularities of the railway track," *Proc. IEEE Conf.*, pp. 1–6, 2023.
- [3]. G. Pradeep, S. U. Kiran, and V. Sathyadurga, "An integrated secure rail system for accident prevention and anti-hijacking measures," in *Proc. Int. Conf. Advances in Data Engineering and Intelligent Computing Systems (ADICS)*, IEEE, 2024, pp. 1–8.
- [4]. Ch. V. Ganesh, N. M. Raslan, M. K. Lafta, C. Lokeshwari, M. Sricharan, and S. Manikanta, "Automated railway track crack detection system utilizing Internet of Things technology for enhanced railway safety," in *Proc. IEEE Int. Conf. Augmented Reality, Intelligent Systems, and Industrial Automation (ARIIA)*, 2024, pp. 1–4.
- [5]. I. Devulapalli, A. V. Vennelakanti, and R. Sallakunta, "Real-time railway track fault detection and environmental monitoring system using Arduino and GSM," in *Proc. 4th Int. Conf. Technological Advancements in Computational Sciences (ICTACS)*, IEEE, 2024, pp. 1410–1415.
- [6]. K. Jayaram, K. P. Meena, K. Sandhiya, and M. Ritheesh, "Implementation of smart alert system to enhance safety near railway tracks," in *Proc. 7th Int. Conf. Inventive Material Science and Applications (ICIMA)*, IEEE, 2025, pp. 812–817.
- [7]. H. Tabassum, S. S. Santolli, S. Sahana, S. A. Rehman, S. Hunagund, and N. H., "Integrated railway infrastructure optimization and control system: Leveraging IoT for advanced railway management and monitoring," in *Proc. IEEE Int. Conf. Electronics, Computing, Communication and Control Technology (ICECCC)*, 2024, pp. 1–6.
- [8]. A. Sharma and H. Babbar, "Implementing gradient boosting techniques for real-time attack detection in vehicular networks," in *Proc. 4th Int. Conf. Technological Advancements in Computational Sciences (ICTACS)*, IEEE, 2024, pp. 213–218.
- [9]. T. Tsunashima, T. Naganuma, and A. Matsumoto, "Condition monitoring of railway tracks using in-service vehicle acceleration measurements," *Measurement*, vol. 45, no. 5, pp. 1100–1110, 2012.
- [10]. A. Molodova, Z. Li, R. Dollevoet, and M. Nunez, "Monitoring of railway track condition using in-service vehicle acceleration data," *Measurement*, vol. 92, pp. 234–245, 2016.
- [11]. J. Lederman, D. Chen, and S. Wang, "Railway track defect detection using sensor fusion and GPS-based localization," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 7, pp. 2243–2252, 2018.
- [12]. H. Han, J. Liu, and Y. Zhang, "Railway surface defect detection based on convolutional neural networks," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 4, pp. 1234–1245, 2020.



- [13]. S. Barua, A. K. Zaman, and M. Rahman, "Machine learning applications in transport asset management and predictive maintenance," *J. Intell. Transp. Syst.*, vol. 24, no. 3, pp. 257–272, 2020.
- [14]. M. Urbano, L. Caggiani, and M. Ottomanelli, "Big data analytics for public transport management and decision support," *Transp. Res. Procedia*, vol. 37, pp. 292–299, 2019.
- [15]. A. Kramarz, J. Cieřła, and P. K. Kramarz, "Reliability and resilience of rail transport systems under disrupted conditions," *Sustainability*, vol. 12, no. 6, pp. 1–18, 2020.