

PREDICTIVE MAINTENANCE OF RAILWAY INFRASTRUCTURE USING ARTIFICIAL INTELLIGENCE

Abstract. The increasing complexity and safety requirements of global railway networks require a transition from traditional manual inspections to advanced data-driven maintenance strategies. This article synthesizes recent advancements in the integration of Artificial Intelligence and Machine Learning for the predictive maintenance of railway infrastructure. It explores a diverse range of methodologies, including Long Short-Term Memory networks for sequential forecasting, Graph Convolutional Network for spatial track analysis, and mobile LiDAR technology for high-precision 3D monitoring. Research findings indicate that these AI-driven approaches can achieve prediction accuracies exceeding 99%. Furthermore, the integration of Deep Reinforcement Learning with Digital Twins has been shown to reduce maintenance activities by 21% and occurring defects by 68%, significantly enhancing operational efficiency. Despite these successes, the article highlights the challenge posed by the “black-box” nature of complex models in safety-critical environments. To address this, the role of eXplainable AI (XAI) frameworks, such as SHAP and LIME, is analysed as a crucial component for fostering trust and ensuring compliance with stringent safety standards like EN 50128. The synthesis concludes that the future of railway management lies in the synergy between robust 3D data acquisition and model interpretability.

Keywords: Predictive Maintenance, Railway Infrastructure, Artificial Intelligence, Machine Learning

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Introduction

The rapid expansion of railway networks globally has introduced significant management complexity, with operating mileages reaching hundreds of thousands of kilometres. Maintaining this vast infrastructure is a safety-critical task where failures can lead to catastrophic damage to infrastructure and risks to human lives (Barbareschi et al., 2025). Traditionally, the inspection of railway components, such as utility poles and track conditions, has relied on manual inspectors, which are increasingly viewed as inefficient and time-consuming (Yan et al., 2025). Consequently, there is a growing shift toward utilizing Artificial Intelligence (AI) and Machine Learning (ML) for service optimization, system monitoring, and predictive maintenance (Barbareschi et al., 2025).

AI technologies offer a transformative opportunity for railway monitoring by enabling tasks such as anomaly detection, track health monitoring, and object identification (Barbareschi et al., 2025; Yan et al., 2025). However, the integration of AI into the railway domain faces two primary challenges: the “black-box” nature of complex ML models and the limitations of traditional monitoring sensors. Many highly accurate models lack determinism and interoperability, making it difficult to satisfy stringent railway safety standards like EN 50128, which require all software behaviours to be statically verified (Barbareschi et al., 2025). Furthermore, traditional 2D image-based detection systems often struggle with dynamic environment adaptability, weather conditions, and visual occlusion (Yan et al., 2025).

To address these barriers, recent research focuses on two innovative fronts. First, the use of eXplainable

Artificial Intelligence (XAI) techniques, such as SHAP (Shapley Additive exPlanations), allows for the construction of human-interpretable explanations for model predictions, fostering trust and compliance (Barbareschi et al., 2025). Second, the adoption of mobile LiDAR (Light Detection and Ranging) technology provides precise 3D point cloud data that remains effective under adverse weather and complex terrain, overcoming the shortcomings of 2D video sequences (Yan et al., 2025).

This article explores a comprehensive approach to railway predictive maintenance by synthesizing these advancements. It examines a framework for explainable time-series forecasting using XGBoost and SHAP for system monitoring, alongside a Dual-Region Adaptive Point Cloud Preprocessing (DAPCP) method for the accurate detection of railway infrastructure components like utility poles (Barbareschi et al., 2025; Yan et al., 2025). By combining interpretability with robust 3D data acquisition, these methods aim to enhance the stability, reliability, and transparency of predictive maintenance in the railway sector.

1. Literature Review

The following literature review summarizes recent research on the application of artificial intelligence and machine learning in railway maintenance, monitoring, and predictive analytics.

1.1. Evolution of Railway Maintenance Paradigms

Railway maintenance strategies have undergone a significant transformation, evolving from reactive

approaches toward data-driven intelligence. Historically, the industry relied on Corrective Maintenance (Run-to-Failure), which involves repairs only after a component fails, leading to high breakdown costs and unplanned downtime (Bris-Peñalver et al., 2026). To mitigate this, Preventive Maintenance (PvM) was introduced, performing tasks at predetermined intervals regardless of the actual asset condition (Bianchi et al., 2025). However, this often leads to unnecessary interventions and increased operational costs (De Simone et al., 2023).

The current shift towards Predictive Maintenance (PdM) and Prescriptive Maintenance (PsM) represents the integration of Industry 4.0 and 5.0 principles. PdM utilizes continuous monitoring to forecast failures before they occur, while PsM goes further by evaluating simulation results to suggest specific automated decisions and maintenance actions (Bris-Peñalver et al., 2026).

1.2. Artificial Intelligence and Machine Learning Techniques

The core of modern railway maintenance lies in Machine Learning (ML) and Deep Learning (DL) methodologies. These are generally classified into three categories: supervised, unsupervised, and reinforcement learning (Hadj-Mabrouk, 2025).

- **Supervised Learning:** Extensively used for defect classification and regression tasks. Long Short-Term Memory (LSTM) networks are preferred for learning long-term dependencies in gradually changing sequential data, such as cooling system trends or track circuit behaviour (De Simone et al., 2023; Bris-Peñalver et al., 2026). Three-based models, including Random Forest and Gradient Boosted Trees (XGBoost), have proven highly effective for predicting the maintenance needs of critical components like railway switches (Allah Bukhsh et al., 2019; Barbareschi et al., 2025).
- **Unsupervised Learning:** Applied primarily for anomaly detection and clustering when labelled data is unavailable (Hadj-Mabrouk, 2025). Online clustering methods allow for continuous health monitoring of sensorized systems by identifying deviations from normal operating profiles in real-time (Le-Nguyen et al., 2023).
- **Reinforcement Learning (RL):** Used for optimizing maintenance schedules and resource allocation (Bris-Peñalver et al., 2026). For instance, the Advantage Actor-Critic algorithm has been applied to reduce defects by choosing optimal maintenance combinations based on cost and safety rewards (Sresakoolchai and Kaewunruen, 2023).

1.3. Monitoring Critical Railway Infrastructure

Research focus varies across different subsystems of the railway network. Track geometry monitoring is one of the most studied areas, utilizing neural networks to predict deterioration based on variables such as traffic speed, load, and historical maintenance (MajidiParast et al., 2025;

Bichanchi et al., 2025). For rolling stock, AI systems monitor axle bearings through temperature forecasting models that combine physical laws with data-driven BP and LSTM networks (Yang et al., 2024). Furthermore, the use of vibration-based monitoring with trackside accelerometers has achieved high accuracy in event detection for switching and crossing sections (Amin et al., 2026).

1.4. Interoperability and Standardization

A significant barrier to AI adoption in railways is the “black-box” nature of high-performing models (Barbareschi et al., 2025; Hadj-Mabrouk, 2025). Safety-critical environments require adherence to standards like EN 50128, which demands deterministic behaviour and static verification (Barbareschi et al., 2025). Consequently, there is a burgeoning field of eXplainable Artificial Intelligence (XAI). Techniques such as SHAP (Shapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) are being integrated into predictive frameworks to provide transparency by quantifying the contribution of individual features to a model’s prediction (Barbareschi et al., 2025; Allah Bukhsh et al., 2019).

2. Methodology

The methodology for implementing AI in railway maintenance follows a structured pipeline consisting of data acquisition, multi-stage preprocessing, and the deployment of specialized machine learning architectures.

2.1. Data Acquisition and Sensing Technologies

Modern railway monitoring utilizes a heterogeneous array of data sources. On-board sensors continuously capture vehicle speed, air spring pressure, and axle box temperatures (Yang et al., 2024). Wayside systems, such as trackside accelerometers, monitor vibration signals to detect critical infrastructure events in switching and crossing sections (Amin et al., 2026). For structural analysis, mobile LiDAR is employed to generate millimetre-level 3D point clouds, which are particularly effective for identifying utility poles and overhead catenary systems under various weather conditions (Yan et al., 2025; Patwardhan et al., 2022). Furthermore, Track Recording Vehicles are used to measure geometric parameters including gauge, alignment, cant, and twist (Bianchi et al., 2025; MajidiParast et al., 2025).

2.2. Preprocessing and Feature Engineering

To ensure high-quality inputs for AI models, raw data undergoes several rigorous preprocessing steps:

- **Cleaning and Filtering:** Inconsistent sampling rates and missing values are addressed using linear interpolation and Butterworth low-pass filters to

remove high-frequency noise (Yang et al., 2024; De Simone et al., 2023).

- **Data Relabelling:** To reduce the rate of false alarms, raw sensor data from bogies is relabelled by identifying steady-state temperature profiles and comparing deviations across multiple sensors within the same bogie (Yang et al., 2024).
- **Point Cloud Preprocessing:** The Dual-Region Adaptive Point Cloud Preprocessing (DAPCP) method partitions scenes into track and non-track regions. Dimensionality reduction via Principal Component Analysis (PCA) and 2D density clustering is then applied to simplify the data while preserving essential features (Yan et al., 2025).
- **Temporal Segmentation:** Continuous data streams are subdivided into time windows, often based on station tops or one-second intervals, to capture recurrent cyclic behaviours (Yang et al., 2024; Amin et al., 2026; Le-Nguyen et al., 2023).

2.3. AI Model Architectures

The research identifies several primary model families suited for different maintenance tasks:

- **Supervised Time-Series Models:** Long Short-Term Memory (LSTM) networks are the preferred choice for learning long-term dependencies in sequential data, such as traction converter cooling trends or bearing temperatures (De Simone et al., 2023; Yang et al., 2024).
- **Tree-Based Classifiers:** Models like XGBoost, Random Forest (RF), and Gradient Boosted Trees are used for predicting maintenance needs and classifying defect severity in switches, achieving high accuracy with structured historical records (Barbareschi et al., 2025; Allah Bukhsh et al., 2019).
- **Graph Neural Networks (GNN):** To model the spatial interdependencies of railway tracks, Graph Convolutional Networks (GCN) and GraphSAGE treat the network as a graph, where information propagates from one segment to neighbouring ones (MajidiParast et al., 2025).
- **Deep Reinforcement Learning (DRL):** The Advantage Actor-Critic algorithm is utilized to optimize maintenance scheduling by allowing an agent to learn optimal intervention combinations based on cost and safety rewards (Sresakoolchai and Kaewunruen, 2023).
- **Online Clustering:** The CHMOC (Continuous Health Monitoring using Online Clustering) method employs DenStream to monitor real-time data streams without prior labels, adapting to temporal evolution and data drift in system health (Le-Nguyen et al., 2023).

2.4. Explainability Frameworks (XAI)

To address safety standards, interpretability techniques are integrated into the pipeline. SHAP

(SHapley Additive exPlanations) is used to quantify the contribution of each input feature to a model's prediction, while LIME (Local Interpretable Model-Agnostic Explanations) provides instance-level justifications for specific maintenance recommendations (Barbareschi et al., 2025; Allah Bukhsh et al., 2019).

3. Results

The application of Artificial Intelligence across different railway subsystems has brought significant improvements in accuracy, operational efficiency, and resource optimization. The results are categorised based on model performance, maintenance efficiency, and computational benchmarks.

3.1. Performance of Predictive and Classification Models

High-precision results have been recorded in the monitoring of critical equipment and infrastructure events:

- **Rolling Stock Monitoring:** The methodology based on Long Short-term Memory (LSTM) network for traction converter cooling systems achieved a failure prediction and forecasting accuracy of over 99 %, with a remarkably low false alarm rate of approximately 0,4 % (De Simone et al., 2023). Similarly, hybrid models for high-speed train axle bearings demonstrated superior performance compared to stand-alone physical or data-driven models in terms of precision, recall, and F1 score (Yang et al., 2024).
- **Event Detection:** In vibration-based monitoring of switching and crossing sections, the Multi-Layer Perceptron archived a peak cross-validation accuracy of 98,89% (Amin et al., 2026). Notably, using Recursive Feature Elimination to reduce dimensionality by 47% (utilizing only 8 features) still maintained a high accuracy of 98,67% (Amin et al., 2026).
- **Track Maintenance Prediction:** Graph Convolutional Network applied to track maintenance reached an accuracy of 99,2%, outperforming standard GraphSAGE models (MajidiParast et al., 2025). For predicting specific maintenance needs in railway switches, Gradient Boosted Trees performed most optimally with an accuracy of 86 %, while Random Forest models achieved 70 % for activity type prediction and 79 % for trigger status prediction on held-out test sets (Allah Bukhsh et al., 2019).

3.2. Maintenance Optimization and Resource Efficiency

Beyond prediction accuracy, AI models have demonstrated a measurable impact on reducing the intensity of maintenance work:

- **Reinforcement Learning Impact:** The integration of the Advantage Actor-Critic algorithm with digital

twins resulted in a 21 % reduction in maintenance activities and a 68% reduction in occurring defects. This suggests that AI-driven agents can learn optimal intervention strategies that are more efficient than traditional planned schedules (Sresakoolchai and Kaerunruen, 2023).

- **Lifetime prediction:** Machine learning models for rail track life prediction, specifically XGBoost and Categorical Boosting, obtained a coefficient of determination (R^2) of approximately 0,81 (Ji et al., 2025). The most reliable predictors for rail life were identified as average temperature, maintenance count, and passenger volume (Jin et al., 2025).

3.3. Computational and Hardware Efficiency

The deployment of AI at the “edge” has shown substantial gains in resource utilization:

- **Edge AI Performance:** Binarized Neural Networks deployed on FPGA platforms for railway fault detection achieved state-of-the-art accuracies of 90,9% and 93,4% (Fu et al., 2025).
- **Cost-Energy Gains:** The FPGA-based system significantly outperformed traditional computing units, achieving a 101,9x improvement in cost-energy efficiency compared to CPUs and 33,8x improvement compared to GPUs (Fu et al., 2025).

3.4. Data Preprocessing Success

Innovative preprocessing frameworks have also proven effective in handling raw, noisy data:

- **Active learning:** The InterCE (Interactive Cycle Extraction) method, which utilizes an ensemble of extractors and expert feedback, was able to produce more reasonable segmentations of sensor data than traditional hand-crafted expert systems (Le-Nguyen et al., 2023).
- **3D Point Cloud Denoising:** The Dual-Region Adaptive Point Cloud Preprocessing (DAPCP) method improved utility pole detection accuracy from 90,3% to 93,6%, confirming that specialized denoising is essential for high-quality feature extraction in complex 3D scenes (Yan et al., 2025).

4. Discussion

The transition toward AI-driven predictive maintenance in railway systems offers transformative potential but is accompanied by significant technical, regulatory, and organizational challenges.

4.1. The Interpretability vs. Accuracy Trade-off

One of the most critical barriers to the adoption of advanced AI models, particularly Deep Learning (DL), is their “black-box” nature. While models like LSTM and complex neural networks achieve high predictive accuracy, they often lack transparency in their internal

reasoning. This opacity is incompatible with stringent safety standards such as EN 50128, which require software behaviours in safety-critical railway applications to be deterministic and statically verifiable (Barbareschi et al., 2025).

To bridge this gap, the integration of eXplainable Artificial Intelligence (XAI) techniques like SHAP and LIME is essential. These frameworks allow engineers to understand the contribution of specific features – such as temperature trends or occupancy data – thereby fostering the trust necessary for human-in-the-loop decision-making (Barbareschi et al., 2025; Allah Bukhsh et al., 2019).

4.2. Data Quality and Fragmentation Challenges

AI models are highly sensitive to the quality and relevance of input data. In many railway organizations, data resides in isolated silos managed by different departments, often stored in non-integrated databases or even paper-based forms. This fragmentation prevents a holistic view of asset health.

Furthermore, real-world data often suffers from missing values, noise, and inconsistent sampling rates, necessitating rigorous preprocessing frameworks like InterCE or specialized filtering (Le-Nguyen et al., 2023; Yang et al., 2024).

4.3. Addressing Data Imbalance with Digital Twins

A fundamental obstacle in training AI for failure detection is that malfunctions are rare events in well-maintained systems, leading to highly imbalanced datasets. This skewness can cause models to fail in identifying critical faults while triggering excessive false alarms (Bianchi et al., 2025; Yang et al., 2024). Digital Twins emerge as a powerful solution by providing virtual environments where faithful failure models can be simulated. These simulations generate the necessary failure data to train predictive models under safe and sustainable conditions (Bianchi et al., 2025; Bris-Peñalver et al., 2026).

4.4. Evolution Towards Prescriptive Maintenance

The current research suggests a shift from merely predicting failures (PdM) to Prescriptive Maintenance (PsM), which recommends specific automated decisions and maintenance actions. By utilizing Deep Reinforcement Learning (DRL) agents that learn from interaction with Digital Twins, system can optimize maintenance schedules based on long-term reward maximization, effectively reducing both costs and defects (Sresakoolchai and Kaewunruen, 2023; Bris-Peñalver et al., 2026).

4.5. Organizational and Strategic Implications

The successful deployment of AI is not merely a technical challenge but a strategic one. It requires a

fundamental rethinking of data governance, the adoption of Common Data Environments, and close collaboration between AI experts and domain-specific infrastructure managers. Only through this integration can AI be moved from isolated laboratory prototypes to real-time asset management platforms (Bris-Peñalver et al., 2026).

Conclusion

The integration of Artificial Intelligence into railway infrastructure maintenance marks a fundamental shift from reactive and preventive models to a data-driven predictive and prescriptive paradigm (Bianchi et al., 2025). This article has synthesized recent advancements, demonstrating that AI methodologies – ranging from LSTM networks for sequence forecasting to Graph Convolutional Networks for spatial analysis – can achieve prediction accuracies often exceeding 99% (De Simone et al., 2023). Furthermore, the adoption of mobile LiDAR technology has provided the high-precision 3D data necessary to overcome the environmental limitations of traditional 2D monitoring (Yan et al., 2025).

The benefits of these technologies extend beyond more accuracy. The research confirms that AI-driven agents, particularly when integrated with Digital Twins, can reduce maintenance activities by 21% and occurring defects by up to 68%, significantly enhancing both operational efficiency and passenger safety. Moreover, the deployment of binarized neural networks on FPGA platforms offers a path toward energy-efficient, real-time “edge” monitoring that is over 100 times more efficient than traditional CPU-based systems (Fu et al., 2025).

Despite these successes, the transition to fully autonomous maintenance remains constrained by the “black-box” nature of complex models and the strict requirements of safety standards such as EN 50128. The integration of eXplainable AI (XAI) frameworks like SHAP and LIME is, therefore, not merely a technical addition but prerequisite for fostering the trust and transparency required by infrastructure managers (Barbareschi et al., 2025; Allah Bukhsh et al., 2019).

In conclusion, the future of railway maintenance lies in the synergy between interpretability and robust data acquisition. By addressing current data fragmentation through Common Data Environments and continuing to refine the interpretability of deep learning models, the railway sector can realize a more resilient, sustainable, and reliable infrastructure (Bris-Peñalver et al., 2026; Bianchi et al., 2025). AI is no longer just an experimental tool but a strategic enabler for the next generation of global railway networks.

Acknowledgment

The paper was supported by the project EUREKA E!2023.20239 – RENOIR - “Optimization of operational management in railway transport using artificial intelligence” at Faculty of Operations and Economics of

Transport and Communication, University of Žilina, Slovakia.

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