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Artificial Intelligence In Railway Systems: A Review Of Track Inspection, Rolling-Stock Health Monitoring, Delay Prediction And Intelligent Scheduling

Pawar Aditya Mahendra[1] Prof. M. R. Kumbhoje[2] Prof. M. C. Kolse[3] Prof. S. K. Said[4]
Department of Artificial Intelligence and Data Science
Jaihind College of Engineering
Pune, Maharashtra, India

Abstract—Railways move enormous numbers of passengers and freight, and their safety and punctuality depend on the condition of tracks, rolling stock and signalling and on effective scheduling. Manual inspection and fixed maintenance cycles struggle with the scale of modern networks and with the need to detect defects before they cause accidents or delays. This paper reviews Artificial Intelligence applications across railway systems. It examines deep convolutional networks and object detectors for automated track and rail-surface defect detection from inspection images, recurrent networks for vibration-based condition monitoring of axle-box bearings and other rolling-stock components, big-data analytics and machine learning for train delay prediction, and optimization and learning methods for real-time rescheduling after disruptions. Automatic train protection, including India's Kavach system, and edge deployment of compressed models on inspection vehicles are discussed. A five-layer architecture comprising multimodal sensing, edge inference, a railway data platform, AI decision support and operations control is proposed, with research gaps, objectives, a comparison of applications and challenges including harsh environments, rare failure data, safety certification and integration with legacy systems. The review concludes that AI can make railways safer, more reliable and more efficient when deployed within rigorous safety frameworks.

Index Terms—Railway systems, track inspection, rail defect detection, predictive maintenance, train delay prediction, rescheduling, deep learning, edge AI

I. INTRODUCTION

Indian Railways operates one of the world's largest networks, carrying millions of passengers every day. A cracked rail, a failing bearing or a signalling fault can cause derailments or long delays, and disruptions propagate quickly across busy routes. Traditional inspection relies on trackmen walking the line and periodic maintenance schedules, which cannot keep pace with network size and traffic.

AI offers ways to inspect continuously, predict failures and replan operations in real time. Ghofrani *et al.* [1] surveyed big data analytics in railway transportation, and Tang *et al.* [2] reviewed AI applications across maintenance, traffic planning and management, safety and autonomous driving in railways. This paper reviews these applications and proposes an integrated AI architecture for railway systems.

II. BACKGROUND AND FUNDAMENTAL CONCEPTS

1. Railway Subsystems

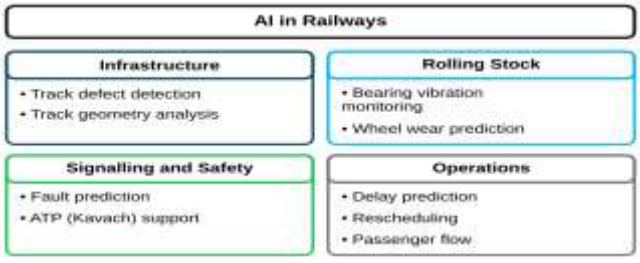


Fig. 1 maps railway subsystems (infrastructure, rolling stock, signalling and operations) to AI applications in each.

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Fig. 1. Railway subsystems and AI applications.

2. Safety Context

Railway systems follow strict safety standards. India's Kavach [3] automatic train protection system prevents signal passing at danger and collisions by automatically applying brakes; AI applications must complement such certified safety systems rather than replace them.

III. LITERATURE SURVEY

Track inspection. Li *et al.* [4] developed a vision system for detecting rail components such as tie plates and spikes and assessing defects from inspection-vehicle images. Faghih-Roohi *et al.* [5] applied deep CNNs to classify rail surface defects such as squats and found deeper networks more accurate. Gibert *et al.* [6] proposed deep multitask learning to detect both crumbling and chipped concrete ties and missing or broken fasteners, improving accuracy over single-task models.

Rolling stock. Lei *et al.* [7] reviewed machinery prognostics applicable to bearings and wheels, and LSTM networks [8] model vibration signals over time for anomaly classification.

Delay prediction. Oneto *et al.* [9] built big-data delay prediction systems using historical running data and weather, and showed improved accuracy over methods used by infrastructure managers.

Rescheduling. Cacchiani *et al.* [10] reviewed recovery models and algorithms for real-time railway rescheduling after disturbances, the basis for AI decision support in traffic control. Modern detectors such as YOLOv8 [11] and compression [12] enable inspection on edge devices mounted on trains. Table I summarizes these works.

TABLE I Summary of Literature Survey

Ref.	Authors	Year	Technique Used	Merits	Demerits
[4]	Li et al.	2014	Vision-based rail component inspection	Automatic detection of track components	Hand-crafted features
[10]	Cacchiani et al.	2014	Review of rescheduling models	Recovery algorithms	Computational complexity
[5]	Faghih-Roohi et al.	2016	Deep CNN rail surface defects	Accurate squat classification	Limited defect types
[6]	Gibert et al.	2017	Deep multitask track inspection	Ties and fasteners jointly	Specific track type
[1]	Ghofrani et al.	2018	Survey of railway big data analytics	Mapped analytics applications	Survey only
[9]	Oneto et al.	2018	Big-data delay prediction	Better than manager methods	Data integration effort
[7]	Lei et al.	2018	Machinery prognostics review	Applicable to bearings	General machinery
[2]	Tang et al.	2022	Review of AI in railways	Broad application mapping	Few deployments

IV. RESEARCH GAP

1. 1) Labelled images of rare but critical defects are scarce.

2. 2) Harsh conditions such as dust, vibration and lighting changes affect sensors and models.

3. 3) Delay prediction and rescheduling are rarely integrated with maintenance data.

4. 4) Safety certification of AI components in signalling is unresolved.

5. 5) Legacy systems limit data access and integration.

1. Objectives

- **O1:** To review AI methods for track inspection and rolling-stock monitoring.

- **O2:** To examine delay prediction and rescheduling approaches.
- **O3:** To propose an integrated AI architecture for railway systems.
- **O4:** To compare AI applications in maturity and impact.
- **O5:** To identify challenges and future directions.

2. Proposed System Architecture

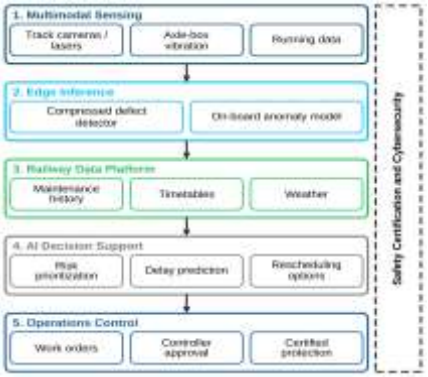


Fig. 2 shows the proposed architecture.

Fig. 2. Proposed AI architecture for railway systems.

3. Multimodal Sensing Layer

Cameras and lasers on inspection vehicles capture track images and geometry; accelerometers on axle boxes record vibration; signalling and train running data are logged.

4. Edge Inference Layer

Compressed detectors on inspection vehicles flag defects in real time; on-board models classify vibration anomalies.

5. Railway Data Platform Layer

Detections, sensor data, maintenance history, timetables and weather are integrated for network-wide analytics.

6. Ai Decision Support Layer

Models prioritize maintenance by risk, predict delays and suggest rescheduling options to controllers.

7. Operations Control Layer

Maintenance teams receive work orders with locations; traffic controllers approve rescheduling; certified protection systems remain in charge of safety.

V. METHODOLOGY AND WORKING

Fig. 3 describes the workflow. Defect detection is evaluated with precision and recall; because missed defects are dangerous, recall for critical classes is prioritized. Maintenance priority for location i can be computed as risk

$$Risk_i = P(failure_i) \times Severity_i \qquad (1)$$

and delay prediction models are evaluated with mean absolute error of arrival time:

$$MAE = (1/n)\ \Sigma\ |t_i - \hat{t}_i| \qquad (2)$$

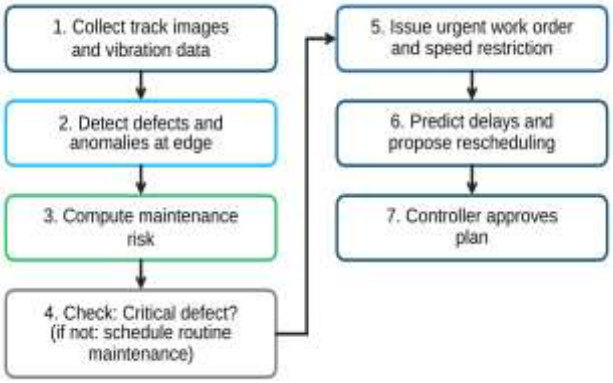


Fig. 3. AI-assisted railway inspection and operations workflow.

VI. COMPARATIVE ANALYSIS

Table II compares AI applications. Track defect detection and bearing monitoring are relatively mature, delay prediction is increasingly deployed, and AI-assisted rescheduling is emerging.

Application	Method	Maturity	Impact
Track defect detection	CNN / YOLO	High	Safety
Bearing monitoring	LSTM / anomaly	Medium –High	Safety, cost
Delay prediction	Big-data ML	Medium	Punctuality
Rescheduling	Optimization + ML	Emerging	Network recovery
Passenger flow	Time-series ML	Medium	Crowd management

TABLE II Comparison of Railway AI Applications

VII. CHALLENGES AND FUTURE SCOPE

Table III summarizes challenges. Future directions include drone-based inspection of bridges and overhead lines, digital twins of rail corridors, passenger-flow prediction for crowd management and AI integration with next-generation signalling.

Challenge	Mitigation
Rare defect data	Augmentation; synthetic defects
Harsh environments	Ruggedized sensors; robust models
Safety certification	AI as advisory; certified ATP
Legacy systems	Data platforms with adapters
Real-time latency	Edge inference with TensorRT-style optimization

TABLE III Challenges and Mitigation

VIII. CONCLUSION

AI can improve railway safety, reliability and efficiency by inspecting infrastructure continuously, predicting rolling-stock failures, forecasting delays and supporting rescheduling. The reviewed literature shows strong results in defect detection and condition monitoring and promising progress in operations. Deploying AI within rigorous safety frameworks, alongside certified protection systems such as Kavach, will allow railways to benefit while maintaining their high safety standards.

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