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A DUAL-LEVEL DATA PROCESSING FRAMEWORK FOR CONDITION-BASED RAILWAY MAINTENANCE: INTEGRATING AUTONOMOUS FLEET INSPECTION AND ADVANCED PROGNOSTICS

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Abstract

The increasing demand for railway network capacity and the necessity to transition from schedule-based to Condition-Based Maintenance (CBM) require infrastructure managers to implement innovative, cost-efficient, and high-frequency monitoring solutions. Traditional human track patrols are costly, subjective, and cannot provide the continuous, high-volume data required for modern, safe operations. This paper proposes a conceptual framework for a data-driven diagnostic system that replaces human track patrols by operating a fleet of autonomous inspection vehicles. These vehicles use high-speed sensors, including advanced vision and ultrasonic systems, to continuously collect large-scale track-condition data, facilitating comprehensive network coverage and condition assessment. The core of the system is a centralized platform that employs Advanced Analytics, Machine Learning, and Artificial Intelligence to automate diagnostics and predict deterioration trends. Critically, architecture uses a dual-level data processing model that explicitly tailors the urgency of operational needs to the complexity of the required analysis. Real-time analysis issues immediate, safety-critical alerts based on precompiled procedures, supporting urgent short-term interventions and real-time operational safety management. Off-line analysis handles complex tasks such as detailed image recognition, advanced trend modelling, and prognostics. This deliberative information is delivered to regional and national infrastructure managers for strategic optimization, long-term asset management, and resource allocation. The framework's key operational advantage is its ability to provide precise, location-specific guidance to field maintenance teams, significantly reducing the time spent searching for suspected defects and enhancing worker safety. This scalable, integrated approach is critical to the global trend towards autonomous, data-centric railway infrastructure management, offering enhanced track availability and optimal allocation of maintenance resources.

Keywords: *unmanned track inspection, automatic track diagnostics, track maintenance decision making*

1 Introduction

The growing demand for railway network capacity, driven by global urbanization and the shift towards green transportation, has placed unprecedented pressure on infrastructure managers to ensure maximum track availability and safety. Traditional maintenance strategies, predominantly based on fixed time intervals or reactive "find and fix" interventions, are increasingly seen as inadequate for modern requirements. The inherent limitations of human-led track patrols, high operational costs, subjectivity of assessment, and safety risks for personnel, necessitate a fundamental paradigm shift [1-3]. The transition from human-centric inspections to automated systems represents a paradigm shift in railway infrastructure management.

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This evolution can be categorized into three primary levels of efficiency: Manual Inspections, Autonomous Track Inspection (ATI) systems, and Dedicated Diagnostic Track Recording Cars (DRMs) [4-6]. Historically, safety standards required human inspectors to conduct “walking patrols” every two weeks.

- Operational capacity: An inspector moves at an average speed of 3–5 km/h. Considering safety protocols and terrain, a single inspector can cover approximately 10–15 km per day.
- Limitations: This method is highly subjective and prone to human error. The literature [7-10] emphasizes that manual patrols often miss sub-visual geometry trends and internal rail defects, providing only a “snapshot” of the track’s condition at a very high labor cost.

Dedicated diagnostic track recording cars (DRM)

Dedicated diagnostic vehicles, equipped with a complete suite of measurement systems (geometry, rail profile, GPR, and ultrasonic); their track condition inspection system can operate autonomously in some cases. The integration of high-speed sensors allows for a comprehensive assessment of the Track Quality Index (TQI), providing objective data that manual patrols cannot replicate [11]:

- Operational capacity: These vehicles typically operate at speeds up to 120–160 km/h
- Performance Gain: A single diagnostic run at 120 km/h covers as much track in 5 minutes as a human inspector covers in an 8-hour shift.

Autonomous track inspection systems (ATI)

ATI systems are diagnostic equipment mounted directly on revenue-earning trains (e.g. ARGUS):

- Operational capacity: these systems operate at line speed (up to 200+ km/h) without requiring dedicated track time.
- The “200x” factor: an ATI system on a daily passenger train provides continuous track monitoring. The cumulative data density is approximately 200 times greater than that of traditional periodic inspections.

Only the diagnostic track recording cars and ATI systems can detect “transient defects” – anomalies that appear only under the dynamic load of a passing train and vanish when the track is unloaded – something a walking inspector cannot identify.

Table 1 Efficiency comparison summary table

Methodology	Inspection speed	Typical frequency	Primary advantage
Manual Patrol	3-5 km/h	B-weekly	Close-up inspections
DRM	80-120 km/h	Monthly/ Quarterly	Comprehensive multi—system data
ATI	100-200 km/h	Daily	Near-continuous stream of track geometry data

As outlined in the proposed framework, the transition from condition-based maintenance (CBM) and ultimately predictive maintenance (PdM) is no longer optional but a strategic imperative. Recent studies indicate that automated track inspection (ATI) systems can detect geometry defects up to 200 times more frequently than traditional visual inspections, providing a statistically superior foundation for infrastructure management. This paper introduces a dual-level data processing framework that bridges the gap between high-frequency data acquisition and actionable maintenance decisions by separating safety-critical real-time alerting from complex, long-term prognostic analysis.

The traditional maintenance paradigm relies heavily on identifying defects only after they have manifested as visible damage. This reactive model is limited by its reliance on human visual inspection, which lacks the frequency and objectivity required for modern high-load networks. In contrast, the transition towards Predictive Maintenance (PdM), the "predict and prevent" philosophy, leverages high-frequency data to identify deterioration trends before they reach critical thresholds.
Recent technological milestones have enabled this paradigm shift. Deep Convolutional Neural Networks (DCNNs) paired with 3D machine vision now enable component-level identification with accuracy exceeding 98%. Unsupervised learning methods, such as autoencoders, have enabled the detection of rail surface anomalies without the time-consuming manual data labelling. Furthermore, high-speed comprehensive inspection systems, such as the CIT450, require parallel computing to handle vast datasets while maintaining accuracy in Track Quality Index (TQI) calculations.

2 Proposed dual-level data processing architecture

The core of the proposed framework is hierarchical architecture that leverages Multi-Agent Systems (MAS) and Edge Computing. The system operates on dual-level logic to balance operational urgency with analytical complexity (figure 1).

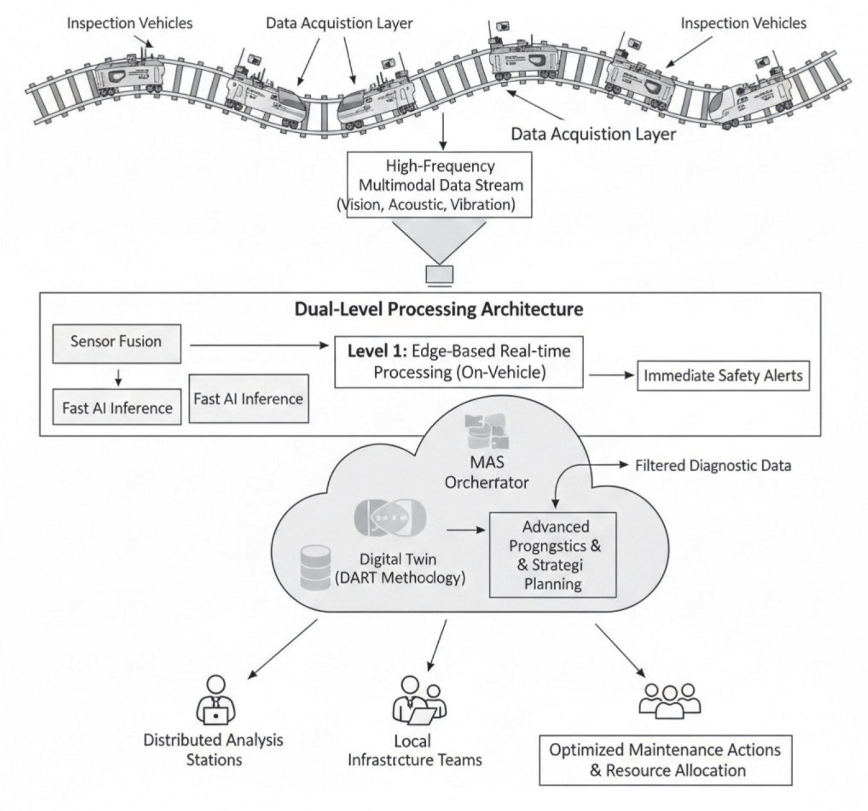

Figure 1 Conceptual framework for a data-driven diagnostic system

The proposed agent-based LLM architecture integrates large language models (LLMs) as the “cognitive core” within a multi-agent system (MAS) framework. This design addresses the critical bottleneck of modern railway diagnostics: the transition from “Big data” (massive streams of geometry measurements) to “Actionable intelligence.” Railway maintenance data is notoriously fragmented, consisting of structured sensor readings (CSV/SQL), semi-structured reports, and unstructured technician notes. LLMs excel at cross-modal data fusion, allowing the system to ingest a technical manual or a hand-written inspection note and correlate it with a 120 km/h laser scan of the track. The goal is to upgrade the diagnostic system from Passive Data collection to Active Reasoning (the LLM as a Reasoning Engine). Traditional diagnostic systems are purely deterministic, operating on fixed thresholds. By incorporating LLMs, the architecture gains semantic reasoning capabilities. The LLM does not merely identify a defect; it interprets it in the context of historical trends, environmental factors, and maintenance logs. which allows the system to move beyond simple “if-then” alerts to complex diagnostic syntheses. The architecture utilizes a decentralized multi-agent approach where specific agents are tasked with distinct roles:

- perception agents: specialized in processing high-frequency raw data from ATI systems
- diagnostic agents: Powered by LLMs to perform “chain-of-thought” reasoning, correlating current geometry defects with past maintenance interventions
- planning agents: tasked with optimizing maintenance schedules by balancing safety urgency with resource availability.

A key justification for this architecture is Explainability. Unlike “black-box” neural networks, an LLM-based agent can provide a natural language justification for its recommendations. For an infrastructure manager, receiving a prompt like: “I recommend immediate tamping at km 142.5 because the rate of twist degradation has accelerated by 15% since the last heavy rain event, ” is far more valuable than a raw error code. The proposed architecture enables the system to “self-triage, ” ensuring that human experts are alerted only to the most critical anomalies, while agents autonomously handle routine monitoring and trend logging.

2.1 Real-time data-oriented reasoning

At the lowest level, the system focuses on raw sensor data. To meet real-time requirements, this level employs Edge Computing nodes located directly on the inspection vehicles. The primary mechanism is based on precompiled procedures and fast-inference AI models. If a critical defect is detected, the system issues an immediate safety-critical alert, minimizing the time between acquisition and reaction (figure 2).

2.2 Deliberative off-line analysis (cloud layer)

Level 2 focuses on complexity. Non-critical data is transmitted to central servers for deeper analysis using the DART (Diagnostics Analysis for Railways and Trams) methodology. Here, a MAS Orchestrator integrates data from various agents to build a Digital Twin. This enables “deliberative planning, ” in which the output is a strategic recommendation, such as predicting the optimal time for rail replacement months in advance:

- Parallel Processing: to manage the “data deluge” from high-speed inspections, Analysis Agents utilize parallel computing to distribute TQI calculations across multiple nodes.
- Digital Twin: a MAS Orchestrator integrates data from various agents to build a Digital Twin. This allows for “deliberative planning, ” predicting optimal times for rail replacement months in advance.

Implementing this architecture redefines the role of maintenance personnel. By automating detection, human labor shifts from low-efficiency "searching" to high-precision "rectifying" actions. The system provides precise, georeferenced guidance based on LiDAR and high-resolution vision data, reducing non-productive time and enhancing worker safety. Diagnostic reliability is further improved through the FusWay architecture, which integrates visual features with acoustic signatures to reduce false positives:

- automation efficiency: deploying a dedicated fleet replaces low-efficiency manual patrols.
- data volume: automated systems identify up to 200 times more geometry defects than traditional visual inspections
- resource optimization: the framework enables optimal allocation of maintenance resources by providing a statistically superior foundation for management.

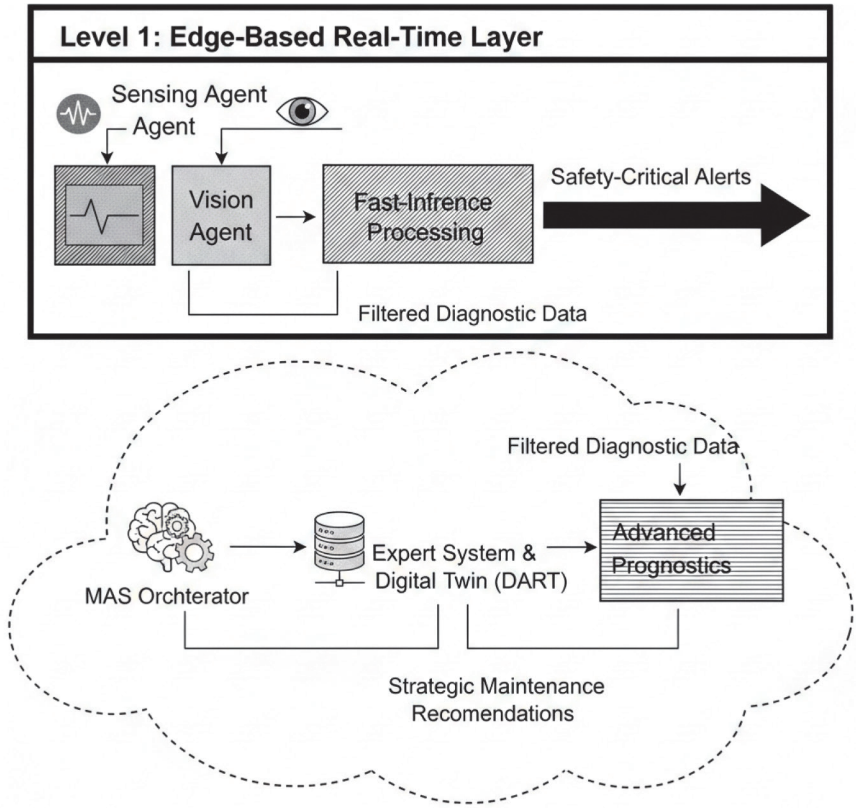

Figure 2 Architecture of the dual-level agent-based system (ABS)

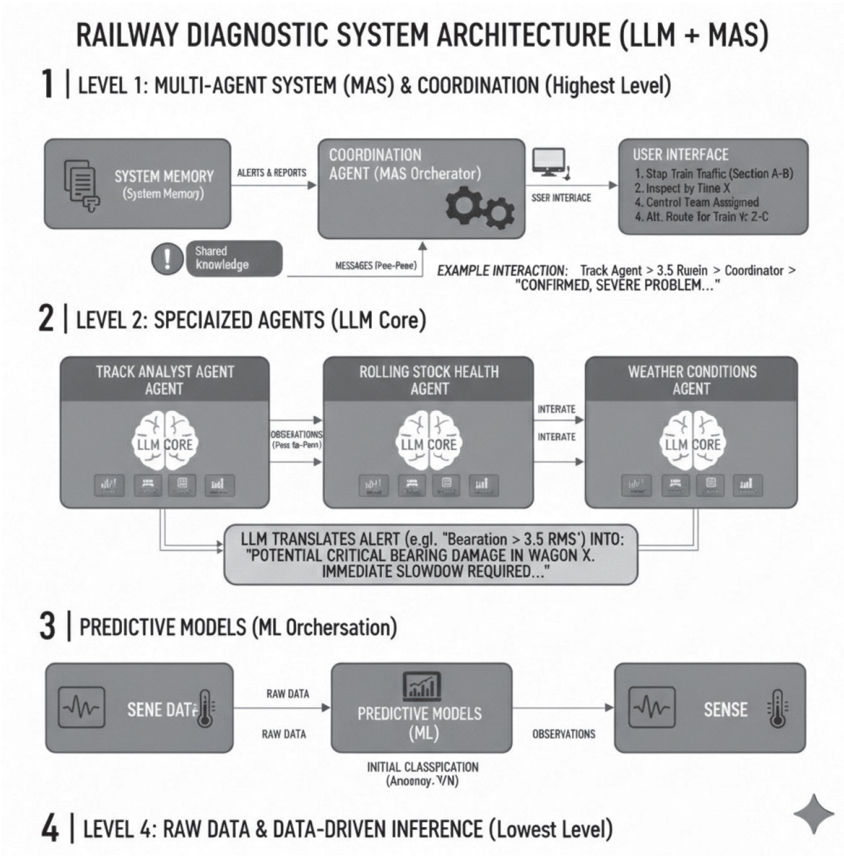

Figure 3 Railway diagnostic system architecture

3 Overcoming computational bottlenecks

The dual-level data processing architecture effectively addresses the “data deluge” by separating operational urgency from analytical complexity. The use of edge computing ensures immediate reactions to safety-critical issues, while the centralized parallel processing layer handles the massive throughput required for network-wide TQI and trend analysis. This approach mitigates the uncertainties of in-service monitoring, ensuring that “predict and prevent” strategies are based on high-fidelity Digital Twins.

4 Conclusion

The framework presented in this paper demonstrates that replacing human patrols with an automated data processing system provides a statistically superior foundation for rail management. The dual-level data processing architecture effectively addresses the “data deluge” by separating operational urgency from analytical complexity. Practical implementation confirms that data-driven maintenance enables more efficient resource allocation and enhanced safety. Future work will focus on refining Hybrid AI models for diverse environments, including railways, metro and tram networks.

References

[1] Puneetha, S., Rakesh, M., Balaji, N., Shashank, D., Chinamayi, P.: Railway track monitoring system using computer vision, International Journal of Scientific Research in Engineering and Management, 9 (2025) 5

[2] Giunta, M., Leonardi, G.: Data-driven track geometry defects localisation and strategies for preventive maintenance: a case study, Transportation Research Procedia, 90 (2025), pp. 234–241

[3] Madejski, J.: DART – Diagnostics analysis for railways and trams: An autonomous tool for track condition assessment, Journal of Materials Processing Technology, 157–158 (2004), pp. 453–458

[4] Esveld, C.: Modern railway track, Second edition, MRT-Productions, Delft, 2001.

[5] Madejski, J., et al.: Diversification of data acquisition and automated inspection as a strategic foundation for railway infrastructure management, International Journal of Railway Engineering, 12 (2025), pp. 88–102

[6] Goldschmidt Group: GRAW secures major contract for track inspection with PKP Polskie Linie Kolejowe S. A., Goldschmidt News, No. 32, 2025.

[7] ProRail: The future of condition monitoring: A vision for the future mix of monitoring devices and systems (MonitorMix), Technical Report, Utrecht, 2025.

[8] FusWay Project Team: Multimodal hybrid fusion approach for automated defect detection using YOLOv8 and Vision Transformers, Technical Documentation, 2025.

[9] Hartmann, T.: Virtual management of complex infrastructure, 4th International Conference on Road and Rail Infrastructure – CETRA 2016, pp. 21–36, Šibenik, Croatia, 23–25 May 2016.

[10] Ahac, M., Lakušić, S.: Track gauge degradation modelling, Urban Transport Systems, 2017., DOI: 10.5772/65086

[11] Popp, K., Kruse, H., Kaiser, I.: Vehicle-track dynamics in the mid frequency range, Vehicle System Dynamics, 31 (1999), pp. 423–464