Proceedings of the Seventh International Conference on
Railway Technology: Research, Development and Maintenance
Edited by: J. Pombo
Civil-Comp Conferences, Volume 15, Paper 10.8
Civil-Comp Press, Edinburgh, United Kingdom, 2026
ISSN: 2753-3239, doi: 10.4203/ccc.15.10.8

An Augmented Reality and Edge AI Framework for Intelligent Railway Pantograph Maintenance Integrating BIM and CMMS

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Abstract

The digital transformation of railway maintenance is increasingly driven by the integration of intelligent technologies capable of improving situational awareness, operational efficiency and knowledge management. Augmented Reality (AR), Artificial Intelligence (AI), Building Information Modelling (BIM) and Computerized Maintenance Management Systems (CMMS) have emerged as key enabling technologies for the development of next-generation maintenance environments aligned with Industry 4.0 and Industry 5.0 paradigms.

This paper presents an integrated augmented reality maintenance assistant combining BIM-based digital models, CMMS maintenance data and real-time object detection using a lightweight MobileNet architecture deployed on mobile devices. The proposed system creates a digital bridge between physical railway assets, AI-based perception and maintenance information systems.

The framework was validated using the pantograph subsystem of the Portuguese Alfa Pendular high-speed train. A MobileNet MultiHW AVG I384 model was trained using operational data and deployed using TensorFlow Lite and MediaPipe for real-time inference.

The model achieved an AP_{50} of 0.9459 and an F1-score of 0.8253. Quantization-Aware Training reduced model size but significantly degraded performance when detecting small industrial components.

The results demonstrate the feasibility of deploying lightweight deep learning models in augmented reality maintenance environments and highlight the potential of integrating AR, edge AI and maintenance information systems for intelligent railway maintenance.

Keywords: railway maintenance , augmented reality , edge AI, MobileNet , BIM , CMMS, object detection

1 Introduction

Railway systems constitute critical infrastructure whose safe and reliable operation depends on effective maintenance strategies. Infrastructure components and rolling stock are exposed to demanding operational and environmental conditions, making the quality of inspection and maintenance essential to ensure safety, availability, and performance throughout their life cycle.

Today, many maintenance activities still rely on fragmented information flows, manual inspection routines, and documentation dependent on technicians. While these practices remain indispensable, they can have certain weaknesses, such as delays in decision-making and an increased risk of inconsistencies between the physical asset, technical documentation, and maintenance records.

The digital transformation of maintenance has been strongly influenced by Industry 5.0 paradigms, which emphasize the integration of intelligent decision-making support, human-centered assistance, and resilient operations [2, 28]. In this context, predictive maintenance, digital twins, augmented reality, and artificial intelligence emerge as particularly relevant technologies for bridging the gap between physical assets and digital maintenance ecosystems [27,32,35].

Augmented reality has generated significant interest due to the way it has improved human-machine interaction during maintenance operations. By superimposing digital information directly into the physical environment, AR systems can support inspection, diagnosis, training, and the execution of procedures in a more intuitive and context-sensitive manner [1,3,13]. Systematic literature reviews indicate that AR is particularly valuable in maintenance scenarios involving spatially complex assemblies, guided navigation, and remote expert support [14–16]. In the railway sector, where assets play a critical role in safety and maintenance work is often carried out under time constraints and operational limitations, this framework is particularly important.

At the same time, advances in computer vision have also enabled increasingly more robust automated recognition of components and operating conditions. Deep convolutional neural networks have demonstrated excellent performance in visual classification and detection problems [4]. However, many high-performance architectures continue to require significant computational power, which sometimes hinders their direct implementation on mobile devices and wearable platforms in real-world maintenance contexts.

Nevertheless, lightweight architectures, such as MobileNet, overcome this limitation by using depth-separable convolutions to reduce computational complexity while preserving good accuracy [5]. These characteristics make them particularly well-suited for deployment, real-time inference, and maintainability. Model optimization techniques, such as quantization, further improve deployability by reducing memory footprint and inference cost, although they may also compromise recognition performance when small industrial components or fine visual details are involved [6].

A second challenge concerns the integration of technologies with maintenance information systems. In many organizations, maintenance history, work orders, and technical records are managed in Computerized Maintenance Management Systems, while digital representations of assets are handled separately through BIM- or CAD-based environments. Research on BIM-enabled operation and maintenance has consistently shown that this separation reduces the potential value of digital models during the life cycle [17–20]. In railway and infrastructure contexts, BIM and related digital asset approaches are increasingly recognised as relevant not only for design and construction, but also for asset management, maintenance planning and data integration [25, 26].

In parallel, digital twin research has reinforced the idea that maintenance systems should connect physical assets, data flows, simulation capabilities and operational intelligence within a unified cyber–physical framework [28, 29]. Recent reviews in the railway sector show that digital twins are being used to improve maintenance strategies, condition monitoring and decision support, particularly when combined with IoT and AI technologies [30, 31]. These developments are leading us to create maintenance environments in which visual perception, asset models, and maintenance records are no longer isolated resources, but rather interconnected components of a single, broader smart infrastructure.

Another emerging area concerns knowledge related to maintenance in textual format. Work orders, inspection reports, and technicians' notes contain relevant information about failure modes, actions taken, and operational decisions. However, this knowledge tends to be underutilized, as it is mostly stored in unstructured formats, making it difficult to organize and retrieve efficiently. Recent studies show that the use of Natural Language Processing techniques, particularly transformer-based approaches, can facilitate the analysis of work orders, semantic search, and knowledge extraction. Additionally, Large Language Models (LLMs) are emerging as a promising solution to support problem-solving and the production of technical documentation [7–12, 33, 34].

In this context, this article proposes an integrated augmented reality maintenance assistant for railway pantograph systems, which combines BIM-based digital models, CMMS maintenance information, and real-time object detection using a lightweight MobileNet architecture. The proposed framework establishes a digital bridge between the physical asset, its digital representation, and its maintenance history, with the aim of directly supporting technicians in the operational environment.

The pantograph subsystem of the Portuguese high-speed train Alfa Pendular was selected as a case study, as it is a critical component in the train's current collection system and requires precise inspection and maintenance procedures. The system is being developed for realistic maintenance conditions, with a focus on the feasibility of combining AR, AI, BIM, and CMMS integration within a railway maintenance workflow.

This paper presents four main contributions. First, it proposes a conceptual architecture for integrated maintenance that combines augmented reality visualization, BIM-based digital asset modeling, integration of data from CMMS systems, and real-time object detection, building upon existing research in these domains. Second, it explores the development of a lightweight detection model based on the MobileNet network, tailored for railway maintenance contexts. Third, it considers the validation of the proposed approach through a pantograph maintenance scenario under realistic conditions. Finally, it analyzes the potential impact of Quantization-Aware Training on detection performance, particularly in industrial contexts involving the recognition of small objects, which constitutes one of the main novel aspects of this work.

2 Research Methodology

This research follows a design-oriented and experimental methodology aimed at developing and validating an intelligent maintenance support system for railway applications. The methodological approach combines system development, data-driven model training and experimental evaluation within a real industrial context. Part of the system architecture and initial integration concepts have been introduced in previous work, including an initial research effort by the same authors [38], where the feasibility of combining augmented reality with maintenance information systems was explored. The present study extends that foundation by focusing on the development, optimisation and experimental evaluation of the object detection component, as well as its integration within a real maintenance scenario.

The research process was structured into four main phases: system conceptualisation, data acquisition and dataset preparation, model training and deployment, and experimental validation.

In the first phase, a conceptual architecture integrating AR, BIM, AI and CMMS was designed. Building on prior work, this architecture aims to enable a seamless connection between physical railway assets, digital models and maintenance information systems. The architecture follows a modular approach, allowing each technological component to operate independently while exchanging information through defined interfaces.

The second phase involved data acquisition and dataset preparation. Visual data were collected from real maintenance operations, followed by frame extraction, manual annotation and data augmentation. A detailed description of the dataset and acquisition conditions is provided in Section 5.

The third phase, which constitutes a core contribution of this work, involved the training of an object detection model based on the MobileNet MultiHW AVG I384 architecture using MediaPipe Model Maker. The training process was conducted using Google Colab with GPU acceleration, with hyperparameters selected empirically to balance training stability and model generalisation. After training, the model was exported to TensorFlow Lite format to enable deployment on mobile devices and edge platforms.

The fourth phase focused on experimental validation of the proposed framework. The trained model was integrated into an Android-based augmented reality application using ARCore and SceneView for spatial tracking and visualisation. The application performs real-time inference using TensorFlow Lite and overlays contextual maintenance information retrieved from the CMMS. This phase extends previous developments by validating the system under realistic operational conditions.

Model performance was evaluated using standard object detection metrics, including Average Precision (AP) and F1-score. Additional experiments were conducted to analyse the impact of Quantization-Aware Training on model performance and deployment efficiency, constituting a further novel contribution of this study.

This methodology enables the evaluation of the feasibility and effectiveness of integrating augmented reality, edge artificial intelligence and maintenance information systems within a railway maintenance environment.

3 Related Work

3.1 Augmented Reality in Industrial Maintenance

Augmented reality has long been recognised as a promising technology for enhancing maintenance activities by aligning digital information with the physical asset under intervention. The foundational survey by Azuma [1] established the conceptual basis of AR systems, while later work demonstrated how this paradigm could support industrial inspection, assembly, training and maintenance in practical settings [3, 13].

Within industrial maintenance, AR has been associated with several expected benefits, including improved spatial understanding, reduced cognitive switching between documentation and equipment, lower error rates and faster execution of guided procedures. Palmarini et al. [14] provided one of the most relevant systematic reviews in this domain, showing that AR can contribute positively to key performance indicators in maintenance tasks, while also identifying persistent barriers related to hardware usability, tracking reliability and content authoring. Jetter et al. [15] similarly examined AR tools for industrial applications and highlighted the importance of measurable operational benefits in real deployment contexts.

Other studies have stressed that AR is especially valuable when maintenance tasks are complex, spatially distributed or require knowledge transfer between experts and field operators. This is particularly visible in remote support scenarios, where AR can facilitate shared situational awareness and collaboration [16]. Even so, many AR-based maintenance systems still depend on manual selection of components, marker-based recognition or relatively constrained operating conditions, which limits their flexibility in real industrial environments.

3.2 Edge AI and Lightweight Object Detection

The increasing maturity of computer vision has created new opportunities for automated recognition of components, states and anomalies during maintenance operations. Deep convolutional neural networks have been central to this progress, with landmark studies showing the remarkable performance of CNN-based (Convolutional Neural NetworK) approaches in visual recognition tasks [4].

For industrial AR applications, however, high predictive performance alone is not sufficient. Models must also operate under hardware constraints associated with mobile devices, embedded platforms and wearable systems. MobileNet was specifically designed for such contexts by adopting depthwise separable convolutions that reduce computational cost while preserving practical accuracy [5]. This makes MobileNet especially relevant for maintenance support applications that require real-time inference directly on the device.

Quantization techniques further support edge deployment by decreasing model size and accelerating inference through low-precision arithmetic [6]. Nevertheless, their effectiveness depends strongly on the application context. In industrial recognition problems involving small objects, subtle geometric distinctions or partially occluded components, the accuracy loss introduced by quantization can become significant. This trade-off is particularly relevant in maintenance scenarios where the correct identification of visually similar or physically small elements has operational consequences.

In parallel with object recognition research, railway and infrastructure studies have increasingly adopted vision-based and model-based techniques for inspection and asset monitoring. Recent work in railway related environments highlights the growing role of machine vision and digital representations for infrastructure measurement, fault detection and maintenance support [36, 37]. These trends reinforce the relevance of lightweight AI perception as a component of intelligent railway maintenance environments.

3.3 BIM, Asset Information and Digital Twins for Maintenance

BIM has progressively expanded beyond the design and construction stages and is now widely discussed as an enabler for operation and maintenance activities. Reviews by Pärn et al. [17], Gao and Pishdad-Bozorgi [18], and Matarneh et al. [19] show that BIM can improve information continuity, maintenance planning, interoperability and lifecycle data accessibility, although implementation barriers remain substantial. Pilot and framework-oriented studies also indicate that BIM becomes considerably more valuable in the operational phase when it is deliberately prepared for facilities management and linked to maintenance workflows [20–22].

In the context of existing assets and maintenance-oriented information management, BIM has also been associated with efficiency gains in inspection, documentation and intervention planning [23, 24]. These findings are particularly relevant for railway assets, where multidisciplinary data, component hierarchies and long lifecycle horizons make integrated information management especially important. Work specifically addressing the railway context also points to the strategic value of BIM for infrastructure coordination, information integration and facility management support [25, 26].

The evolution from BIM-based asset representations toward digital twins has further broadened the scope of maintenance intelligence. Digital twins are described as cyber–physical environments that combine real-time data, virtual representations, analytics and decision support [27–29]. Recent reviews on AI-enhanced digital twins and railway digital twin applications indicate that these frameworks are becoming central to predictive maintenance, condition monitoring and system-level optimisation [30, 35]. In railway maintenance specifically, IoT-enabled monitoring and integrated asset data platforms have been identified as important enablers for more proactive and data-centric strategies [31].

3.4 Natural Language Processing and LLMs

While computer vision supports the interpretation of physical assets, maintenance operations also generate extensive textual documentation, including work orders, inspection reports, intervention records and technician notes. These texts encode valuable operational knowledge, but their practical use is often limited by inconsistent terminology, abbreviations and the unstructured nature of maintenance language.

Natural Language Processing (NLP) has therefore become an increasingly relevant research direction in maintenance engineering. Mo et al. [7] showed that NLP can support automated workforce assignment in maintenance management, while Li et al. [8] demonstrated that maintenance work orders can be analysed to improve intervention planning and resource allocation. A recent systematic literature review by Zhong et al. [33] confirms the rapid expansion of NLP applications in industrial maintenance, including classification, information extraction, semantic analysis and knowledge discovery from maintenance texts.

Transformer-based semantic search has further expanded these possibilities, enabling relevant maintenance knowledge to be retrieved from large sets of historical records without relying on rigid keyword matching [9]. Other recent work has explored how maintenance actions described in free text can be decomposed into meaningful sub-tasks, revealing new opportunities for procedural standardisation and knowledge reuse [34].

Large Language Models add another layer of capability by enabling more natural interaction with maintenance information systems. Recent studies show promising results in troubleshooting assistance, collaborative human–machine diagnosis and multimodal knowledge integration for industrial operation and maintenance [10, 11]. In parallel, NLP and LLM-based approaches are also being explored for generating structured industrial documentation and technical reports, which is directly relevant to inspection reporting and maintenance traceability [12, 35].

For the present railway maintenance context, this line of research is particularly relevant. A future extension of the proposed framework could use LLM-based support to interpret work orders written in natural language, retrieve similar historical interventions from the CMMS and assist technicians in completing inspection reports in a more consistent and traceable way. However, because railway maintenance is safety-critical, such support should be designed as supervised assistance rather than autonomous decision-making.

4 System Architecture

The proposed system integrates four technological layers connecting physical railway assets with digital maintenance systems, as illustrated in Fig. 1.

The CMMS layer is implemented using the Odoo Maintenance platform and manages maintenance work orders, intervention history and asset information.

The BIM layer contains digital models of pantograph components created in Blender and exported to glTF format.

The AI perception layer performs object detection using a MobileNet MultiHW AVG I384 architecture integrated with a RetinaNet-style detection head.

The augmented reality layer is implemented using Android Studio, ARCore and SceneView, enabling real-time rendering and contextual visualisation of detected components.

5 Dataset and Data Preparation

The dataset used in this study was collected during maintenance operations performed in railway maintenance facilities, with a specific focus on the pantograph subsystem of the Portuguese Alfa Pendular high-speed train. This component plays a critical role in current collection from the overhead catenary system, making it particularly relevant for inspection and maintenance support applications.

Video data were acquired using a Samsung Galaxy S22 smartphone to replicate the operational conditions expected for a mobile augmented reality maintenance system. The acquisition process was conducted under realistic working conditions, including variations in illumination, partial occlusions, and different viewing perspectives. These factors were intentionally preserved in the dataset to ensure that the trained model reflects real-world operational challenges.

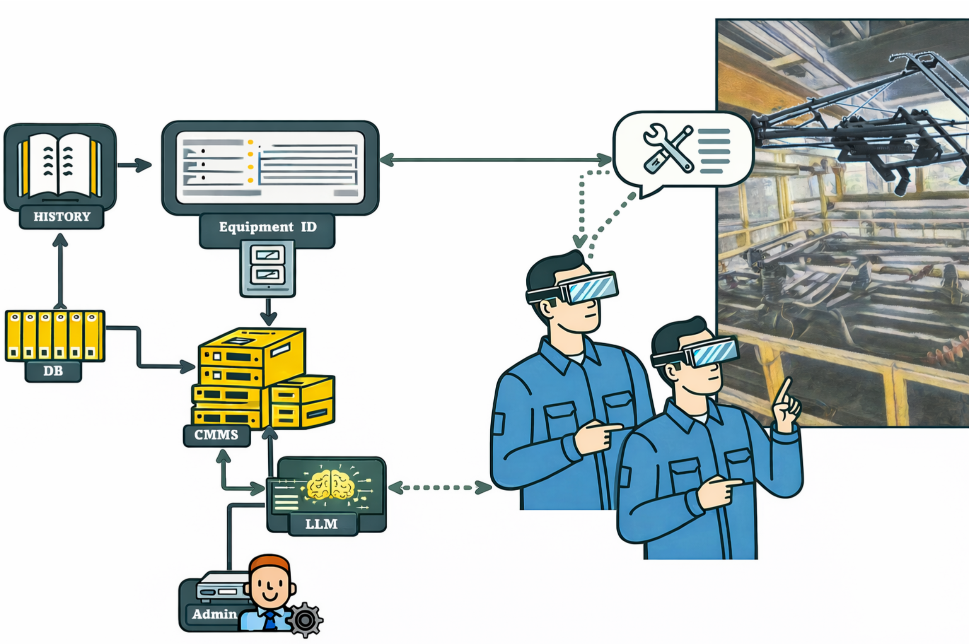

Figure 1: Diagram of the proposed system architecture and workflow, illustrating the integration of historical data, CMMS, and Large Language Models (LLMs) to support intelligent maintenance operations. The process is divided into two main flows: (i) data acquisition and management, including equipment identification and maintenance history, and (ii) intelligent processing and user interaction through LLMs. The LLM module enables the generation and contextualisation of maintenance work orders and instructions, which are delivered in real time to technicians via an AR mobile application. The system supports enhanced decision-making and improved efficiency in railway maintenance environments.

Recorded videos were processed through frame extraction, followed by manual annotation using the Visual Object Tagging Tool (VoTT). Each annotation consisted of bounding boxes associated with maintenance-relevant pantograph components. The dataset comprises annotated object instances distributed across four classes: *pantograph structure*, *cleaned brushes*, *uncleaned brushes*, and *grounding connector*. A quantitative description of the dataset composition is provided in Table 1. Additional collection and annotation details were reported in a previous manuscript by the authors.

The dataset was divided into training, validation, and testing subsets. The distribution of object instances per class was kept as balanced as possible within the constraints of real maintenance data collection.

To improve dataset diversity and model generalisation, data augmentation was applied only to the training subset. Augmentation was performed using the Roboflow platform and included image rotation, horizontal flipping, scaling, contrast adjustments, and illumination variations. No augmentation was applied to the validation or testing subsets, in order to preserve an unbiased evaluation of model performance.

Finally, the annotated dataset was exported in COCO format to ensure compatibility with the deep learning training pipeline adopted in this work.

Table 1: Distribution of images and annotated object instances in the dataset.

Class	**Total Instances**	**Training**	**Validation**	**Testing**
Pantograph structure	654	567	58	29
Cleaned brushes	571	549	19	11
Uncleaned brushes	521	447	49	25
Grounding connector	285	251	21	13
Total	2031	1814	147	78

6 Model Training and Implementation

The object detection model was trained using the MobileNet MultiHW AVG I384 architecture within the MediaPipe Model Maker framework. The training process was conducted in a Google Colab environment equipped with an NVIDIA Tesla T4 GPU, enabling efficient experimentation and model optimisation.

The dataset described in Section 5 was used as input, with annotated images split into training and validation sets. The training process was configured with 30 epochs, a batch size of 8 and a learning rate of 0.3. These hyperparameters were selected empirically to achieve a balance between training stability and model convergence. During training, loss curves were monitored to ensure stable optimisation behaviour and to detect potential overfitting.

Once training was completed, the model was exported to TensorFlow Lite format to enable deployment on mobile and edge devices. This format allows efficient on-device inference with reduced memory and computational requirements.

The TensorFlow Lite model was then integrated into the augmented reality mobile application developed using Android Studio. Real-time inference is performed directly on the device, allowing the system to detect pantograph components in camera frames and overlay contextual maintenance information retrieved from the CMMS.

Table 2: Distribution of annotated object instances across the dataset splits.

Class	**Total**	**Training**	**Validation**	**Testing**
Pantograph Brushes	654	567	58	29
Uncleaned Brushes	521	447	49	25
Cleaned Brushes	571	549	19	11
Ground Connector	285	251	21	13

7 Experimental Evaluation

The performance of the object detection model was evaluated using standard metrics commonly employed in object detection tasks, namely Average Precision (AP), precision, recall, and F1-score. These metrics were used to assess both the overall detection capability of the model and the balance between correct detections and missed or incorrect predictions.

Average Precision measures the area under the precision–recall curve and provides a comprehensive evaluation of detection performance across different confidence thresholds. In this study, the baseline model achieved an AP_{50} value of 0.9459, indicating strong detection performance under realistic operational conditions. As shown in Table 3, the corresponding precision and recall values for the validation process were 0.7970 and 0.8562, resulting in an F1-score of 0.8253.

For contextual interpretation of these results, the class distribution of the dataset is presented in Table 2. As can be observed, the dataset includes four maintenance-relevant classes with different numbers of annotated instances, which should be taken into account when analysing detection performance.

The global evaluation metrics obtained for both the baseline validation process and the Quantization-Aware Training (QAT) version are summarized in Table 3. The results show that the trained MobileNet model is capable of accurately detecting pantograph components in realistic maintenance scenarios. However, they also show that the QAT version led to a severe degradation in performance, with precision decreasing to 0.028, recall to 0.243, and the F1-score to 0.0502.

Table 3: Comparison of precision, recall and F1-score values for the baseline validation model and the QAT model.

Process	Precision	Recall	F1-score
Validation	0.7970	0.8562	**0.8253**
QAT	0.0280	0.2430	**0.0502**

Additional experiments were conducted to analyse the impact of Quantization-Aware Training on model size and computational performance. Although quantization reduced model size and improved inference efficiency, the comparison presented in Table 3 shows that this optimisation came at the cost of a substantial loss in detection accuracy. This effect was particularly critical in the present industrial context, where reliable recognition of relatively small components is essential for maintenance support.

Examples of detection outputs on representative validation images are presented in Fig. 2, illustrating both successful recognition cases and visually challenging situations involving occlusions, illumination changes, and small components.

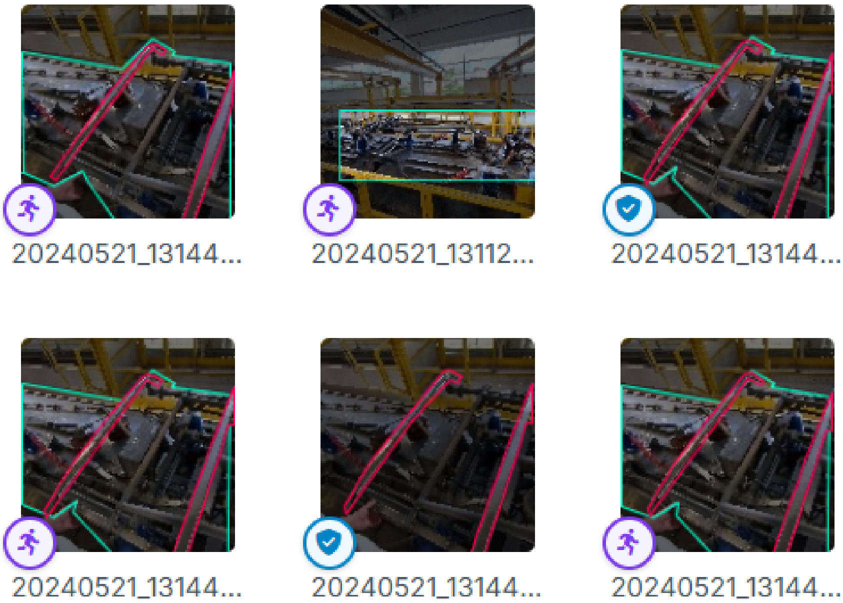

Figure 2: Examples of images from the dataset. The images are organized in two rows with three images each. The first (top left), second (top center), fourth (bottom left), and sixth (bottom right) images correspond to the training set, while the third (top right) and fifth (bottom center) images belong to the validation set. Each image has visual annotations that indicate trajectories and classes associated with the actions or elements observed in the scene, as represented by the circular icons.

8 Discussion

The results of this study indicate that lightweight convolutional neural networks have the potential to be applied in maintenance contexts supported by augmented reality.

The integration of AI-based perception mechanisms, BIM models, and data from CMMS systems points toward the creation of more context-aware maintenance workflows, enabling technicians to access relevant information during inspection activities.

Additionally, it is anticipated that future maintenance systems could benefit from the incorporation of large language models, capable of analyzing technical documentation and supporting report generation.

Recent research on BIM-enabled operation and maintenance, digital twins and railway asset monitoring suggests that the real value of intelligent maintenance systems does not arise from a single technology in isolation, but from the structured integration of perception, asset information and historical maintenance knowledge [18, 19, 30, 31]. In this sense, the proposed architecture is relevant not only because it supports real-time visual recognition, but also because it establishes a practical connection between the physical component, its BIM representation and its CMMS record.

Although quantization is advantageous for implementation on devices with limited resources, it can lead to performance losses in industrial settings. In particular, techniques that perform well in general benchmarks may not maintain the same level of accuracy when detecting small, partially occluded, or visually similar objects [6]. In maintenance contexts, such losses are not merely statistical, they may compromise the usefulness of the assistance system during real interventions.

A further implication concerns the role of maintenance text. The recent literature on NLP and LLMs in maintenance indicates that textual maintenance records should be considered a strategic source of knowledge rather than a passive administrative by-product [9,10,12,33]. For railway applications, this opens a relevant path for combining computer vision, BIM and CMMS data with language-based assistance capable of interpreting work orders, retrieving similar intervention histories and helping technicians complete inspection reports more consistently.

9 Conclusion

This paper presents an augmented reality maintenance assistant that integrates BIM models, CMMS data and real-time object detection using a lightweight deep learning approach. The framework creates a digital connection between physical railway assets, their digital representations and maintenance information, enabling contextualised support directly in operational settings.

Experimental validation on the pantograph subsystem of the Alfa Pendular train shows that lightweight models, such as MobileNet, can run effectively on mobile devices for real-time detection, supporting the use of edge AI in maintenance scenarios. However, the results also indicate that while quantization improves efficiency, it may reduce accuracy when detecting small industrial components.

Overall, the approach highlights the potential of combining augmented reality, edge AI and maintenance information systems to enhance inspection processes, access to information and technician support, providing a basis for more advanced intelligent maintenance platforms.

References

[1] R.T. Azuma, "A survey of augmented reality", Presence: Teleoperators & Virtual Environments, 6(4), 355–385, 1997.

[2] J. Lee, B. Bagheri, H.-A. Kao, "A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems", Manufacturing Letters, 3, 18–23, 2015.

[3] X. Wang, S.K. Ong, A.Y.C. Nee, "A comprehensive survey of augmented reality assembly research", Advances in Manufacturing, 4(1), 1–22, 2016.

[4] A. Krizhevsky, I. Sutskever, G.E. Hinton, "Imagenet classification with deep convolutional neural networks", Advances in Neural Information Processing Systems, 25, 2012.

[5] A.G. Howard et al., "MobileNets: Efficient convolutional neural networks for mobile vision applications", arXiv preprint arXiv:1704.04861, 2017.

[6] B. Jacob et al., "Quantization and training of neural networks for efficient integer-arithmetic-only inference", Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2704–2713, 2018.

[7] Y. Mo et al., "Automated staff assignment for building maintenance using natural language processing", Automation in Construction, 113, 103150, 2020.

[8] Y. Li et al., "Automated analysis and assignment of maintenance work orders using natural language processing", Automation in Construction, 165, 105501, 2024.

[9] S.M.R. Naqvi et al., "Unlocking maintenance insights in industrial text through semantic search", Computers in Industry, 157, 104083, 2024.

[10] S. Wen et al., "Leveraging large language models for Human-Machine collaborative troubleshooting of complex industrial equipment faults", Advanced Engineering Informatics, 65, 103235, 2025.
[11] Z. Zhang et al., "A knowledge graphs construction method enhanced by multimodal large language model for industrial equipment operation and maintenance", Advanced Engineering Informatics, 68, 103705, 2025.
[12] I. Rojek et al., "Natural Language Processing in Generating Industrial Documentation Within Industry 4.0/5.0", Applied Sciences, 15(23), 12662, 2025.
[13] S.K. Ong, A.Y.C. Nee, Virtual and Augmented Reality Applications in Manufacturing, Springer, 2013.
[14] R. Palmarini et al., "A systematic review of augmented reality applications in maintenance", Robotics and Computer-Integrated Manufacturing, 49, 215–228, 2018.
[15] J. Jetter et al., "Augmented reality tools for industrial applications: What are potential key performance indicators and who benefits?", Computers in Human Behavior, 87, 18–33, 2018.
[16] B. Marques et al., "Remote collaboration in maintenance contexts using augmented reality: insights from a participatory process", International Journal on Interactive Design and Manufacturing, 16(1), 419–438, 2022.
[17] E.A. Pärn et al., "The building information modelling trajectory in facilities management: A review", Automation in Construction, 75, 45–55, 2017.
[18] X. Gao, P. Pishdad-Bozorgi, "BIM-enabled facilities operation and maintenance: A review", Advanced Engineering Informatics, 39, 227–247, 2019.
[19] S.T. Matarneh et al., "Building information modeling for facilities management: A literature review and future research directions", Journal of Building Engineering, 24, 100755, 2019.
[20] P. Pishdad-Bozorgi et al., "Planning and developing facility management-enabled building information model (FM-enabled BIM)", Automation in Construction, 87, 22–38, 2018.
[21] J. Patacas et al., "BIM for facilities management: A framework and a common data environment using open standards", Automation in Construction, 120, 103366, 2020.
[22] L. Li et al., "Developing a BIM-enabled building lifecycle management system for owners: Architecture and case scenario", Automation in Construction, 129, 103814, 2021.
[23] A. Salzano et al., "Existing assets maintenance management: Optimizing maintenance procedures and costs through BIM tools", Automation in Construction, 149, 104788, 2023.
[24] R. Marmo et al., "Building performance and maintenance information model based on IFC schema", Automation in Construction, 118, 103275, 2020.
[25] M. Bensalah et al., "Overview: the opportunity of BIM in railway", Smart and Sustainable Built Environment, 8(2), 103–116, 2019.
[26] Z. Liu et al., "Decision support for railway track facility management using OpenBIM", Automation in Construction, 168, 105840, 2024.
[27] Q. Qi, F. Tao, "Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison", IEEE Access, 6, 3585–3593, 2018.
[28] Y. Lu et al., "Digital Twin-Driven Smart Manufacturing: Connotation, Reference Model, Applications and Research Issues", Robotics and Computer-Integrated Manufacturing, 61, 101837, 2020.
[29] M. Soori et al., "Digital twin for smart manufacturing: A review", Sustainable Manufacturing and Service Economics, 2, 100017, 2023.
[30] E.A. Thompson et al., "Revolutionizing railway systems: A systematic review of digital

twin technologies", High-speed Railway, 2025.
[31] A.-Q. Gbadamosi et al., "IoT for predictive assets monitoring and maintenance: An implementation strategy for the UK rail industry", Automation in Construction, 122, 103486, 2021.
[32] P. Mallioris et al., "Predictive Maintenance in Industry 4.0: A Systematic Multi-Sector Review and Decision Support Perspective", Procedia CIRP, 123, 208–213, 2024.
[33] K. Zhong et al., "Natural language processing approaches in industrial maintenance: A systematic literature review", Procedia Computer Science, 232, 2082–2097, 2024.
[34] V. Giordano, G. Fantoni, "Decomposing maintenance actions into sub-tasks using natural language processing: A case study in an Italian automotive company", Computers in Industry, 164, 104186, 2025.
[35] S. Chen et al., "AI-Enhanced Digital Twins in Maintenance: Systematic Review and Industry Perspective", Computers & Industrial Engineering, 204, 110881, 2025.
[36] J. Wu et al., "Track gauge measurement based on model matching using UAV image", Automation in Construction, 155, 105070, 2023.
[37] A. Kumar, S.P. Harsha, "A systematic literature review of defect detection in railways using machine vision-based inspection methods", International Journal of Transportation Science and Technology, 18, 207–226, 2025.
[38] A. Malta et al., "Survey on the use of BIM methodology for railway 3D modeling", Discover Applied Sciences, 6(12), 657, 2024.