frontiers | Frontiers in Mechanical Engineering

TYPE Review
PUBLISHED 07 January 2026
DOI 10.3389/fmech.2025.1722114

Check for updates

OPEN ACCESS

EDITED BY
Lien Thi Vu,
Phenikaa University, Vietnam

REVIEWED BY
Luis Osvaldo Rojas Valdivia,
Pontificia Universidad Católica de Valparaíso, Chile
Daniel Campos Olivares,
SAP SE, Germany

*CORRESPONDENCE
Ilesanmi Daniyan,
afolabiilesanmi@yahoo.com

RECEIVED 10 October 2025
REVISED 10 November 2025
ACCEPTED 14 November 2025
PUBLISHED 07 January 2026

CITATION
Azeta J, Omeche TT, Daniyan I, Abiola JO, Daniyan L, Phuluwa HS and Muvunzi R (2026) Artificial intelligence and robotics in predictive maintenance: a comprehensive review. *Front. Mech. Eng.* 11:1722114. doi: 10.3389/fmech.2025.1722114

Artificial intelligence and robotics in predictive maintenance: a comprehensive review

Joseph Azeta[1], Theodore Tochukwu Omeche[1], Ilesanmi Daniyan[1,2,3]*, Johnson Opeyemi Abiola[1], Lanre Daniyan[4], Humbulani Simon Phuluwa[3] and Rumbidzai Muvunzi[5]

[1]Department of Mechatronics Engineering, Faculty of Engineering, Bells University of Technology, Ota, Nigeria, [2]Centre for Artificial Intelligence, Bells University of Technology, Ota, Nigeria, [3]Department of Industrial Engineering and Engineering Management, University of South Africa, Florida, South Africa, [4]Centre for Basic Space Science, University of Nigeria, Nsukka, Nigeria, [5]School of Mechanical, Industrial and Aeronautical Engineering, University of Witwatersrand, Johannesburg, South Africa

The integration of artificial intelligence (AI) and robotics into predictive maintenance (PdM) systems has brought about a fundamental change in the operations of the industries since it has left behind the previous method of reactive and scheduled maintenance models in favor of proactive and data-driven models. The current systematic review of literature (2015-2025) is aimed at the development of PdM, in which AI techniques, machine learning, sensor technology, and the incorporation of robotics contribute to more efficient systems and address the difficulties in their implementation and implications for the future of industries. The findings show that the support vector machines and neural networks with supervised learning algorithms are very accurate in fault classification and the remaining useful life prediction. On the other hand, the methods of unsupervised learning can be applied in the detection of anomalies in cases where a limited quantity of labelled data exists. Examples of deep learning architectures that are more effective in processing more complex sensor data, as well as time-series patterns, include convolutional neural networks (CNNs) and long short-term memory (LSTM) networks. Moreover, sensor systems that are already linked to the IoT provide the ability to monitor in real time, and this significantly improves fault detection. The AI-based PdM systems in combination are highly rewarded with reduced downtime, longer equipment life, and enhanced maintenance scheduling. There are still, however, concerns about data quality, computation loads, and implementation cost that remain a major barrier to common usage. The future of AI should be on explainable AI, hybrid modelling techniques, and enhanced sensor technology to render AI scalable, interpretable, and more industry-applicable.

KEYWORDS

anomaly detection, artificial intelligence (AI), machine learning (ML), industry 4.0, internet of things (IoT) sensors, predictive maintenance, robotics

1 Introduction

Predictive maintenance (PdM) has now become one of the bedrocks of Industry 4.0 technology for enhancing equipment reliability, availability and extended useful life. This technique leverages condition monitoring, data analytics, and prognostics to predict failures so that schedule maintenance operations can be effectively scheduled before a costly breakdown (Ucar et al., 2024). Traditionally maintenance operation is driven by human experience or preventive strategies such as oil or vibration analysis, routine or periodic inspections. This sometimes prove ineffective, inaccurate, costly and may lead to expensive machine breakdown. The advent of PdM allows the use of algorithms for data analytics in order to determine the time to maintenance (Daniyan et al., 2020; Daniyan et al., 2021). PdM is useful in cost-effective maintenance solution that enables operators take a proactive approach before equipment breakdown. Furthermore, the modern industrial environment principally driven by data requires more advanced maintenance plans because of the growing complexity of the manufacturing systems. The rise in the costs of operation, and the urgent necessity to maintain production in an uninterrupted state necessitate a reliable techniques for machine diagnostics and prognostics operations (Daniyan et al., 2020). Conventional methods of maintenance, such as reactive (run-to-failure) and preventive (scheduled) maintenance, can no longer cope with the manufacturing trends and complexities. Hence, to avoid unwarranted downtime, over-maintenance, or unexpected failures, which can be both costly in terms of financial loss and safety issues, there is a need for a data-driven maintenance technique such as PdM.

Artificial intelligence (AI) and robotics are also technologies that have gained traction in Industry 4.0, enabling automated, data-driven diagnostics and prognostics, as well as intervention (Vachtsevanos et al., 2006; Schwabacher and Goebel, 2007; Sikorska et al., 2011). The high rate of development of robotics and artificial intelligence systems has generated significant changes in industrial processes and has a direct effect on predictive maintenance systems. While AI finds various applications in smart manufacturing such as predictive analytics (Daniyan et al., 2022), robotics automation makes operations more productive in the workplaces where automated activities are needed, and also reduces the danger to workers on their safety and allows permanent operation (Pookkuttath et al., 2021). Such convergence of technologies is a paradigm shift from the old ways of maintenance to smart, data-driven mechanisms that are capable of predicting and avoiding equipment failures before they happen.

Predictive maintenance now substitutes the old reactive and planned approaches to maintenance through instantaneous data analysis, computational learning, and advanced sensor technologies. The use of AI allows industries to predict the failure of the equipment in advance, construct more effective maintenance plans and minimize the downtime of the operating equipment, and increase its service life (Kamel, 2022; Mourtzis et al., 2023).

PdM leverages AI to detect anomalies and predict remaining useful life (RUL) of an equipment, while robotics offers an automated sensing and intervention especially in an hazardous or difficult-to-reach locations. The convergence of AI, robotics, and other Industry 4.0 technologies such as the smart sensor, Internet-of-Things (IoT) and digital twin promises a fully integrated maintenance loop whereby there is a culture of continuous data collection, analytics, monitoring, prediction and automated intervention or human-supervised action.

Many studies have reported on the suitability of AI for predictive analytics and PdM operations (Zenisek et al., 2019; Kumar and Hati, 2021; Shah, et al., 2021; Betz et al., 2022; Bouabdallaoui et al., 2021). For instance, machine and deep learning have been applied for intelligent fault diagnosis (Duan et al., 2018; Li et al., 2020; Zhou et al., 2022) and AI-models have been employed for prognostic operations (Daniyan et al., 2020; Daniyan et al., 2023; Kamariotis et al., 2024). Raouf et al. (2023) reported on the use of transfer learning; an emerging AI technique for fault diagnosis while Adam et al. (2023) found that the deep learning can be utilized for diagnosing multiple faults in an equipment or system. Yin et al. (2023) reported on transfer network for fault diagnosis while some authors have explored the emerging field of explainable AI for predictive analytics and maintenance as well as in smart manufacturing (Matzka, 2020; Hrnjica and Softic, 2020; Garouani et al., 2022). In the field of intelligent manufacturing, Yan et al. (2023) as well as Liu et al. (2021) have demonstrated the application of AI for predictive maintenance.

The use of robots for maintenance operations has also been reported. For instance, Daniyan et al. (2023) reported on the design of robot for inspecting and diagnosis of rail track defects while the use of robots for pipeline defects assessment and detection has been reported (Nguyen et al., 2025; Daniyan et al., 2022). Mitrevski and Plöger (2019) reported on a data-driven robotic system for diagnostics operation and fault identification while the use of AI systems and models for troubleshooting robots to identify faults and anomaly have been reported (Chen et al., 2020; Hong, et al., 2020).

However, the integration of AI and robotic systems for PdM is still an emerging field of research with a view to integrate data analytics and predictive capabilities of AI models with autonomous intervention of robotic systems.

Hence, the following are the research questions underlying this study:

1. What are the AI methods and data modalities employed for PdM?
2. What robotic capabilities support the implementation of PdM for maintenance operations such as inspection, and repair, etc.?
3. How can the integration of AI and robotics be achieved?
4. What are the current limitations and adoption hindering the deployment of AI and robotics for PdM and what are the future trends?

This literature review provides in-depth study of the history of predictive maintenance, focusing on how AI and robotics can make predictive maintenance more effective, how adoption issues can be mitigated, and the future possible future trends. The paper also uses the latest studies to offer a profound understanding of the influence of AI-controlled robots on predictive maintenance within the commercial environment in different sectors such as manufacturing, aerospace, automotive, and energy industries. It synthesizes the findings of studies on the intersection and integration of AI and robotics for predictive maintenance, highlighting the techniques employed, data and algorithmic trends, robotic roles, integration architectures, evaluation metrics, deployment challenges and limitations, as well as future research opportunities.

This study is significant in that it contributes to the understanding how AI and robotics are deployed in PdM. It also contributes a conceptual model for ai-robot integration for predictive maintenance. The synthesis of literature provides multidisciplinary knowledge on the diagnostics and prognostics capability of AI and robotic inspection and intervention, thus, providing a consolidated reference for researchers, practitioners, and policymakers.

From the theoretical perspective, this study advances the conceptual understanding of a form of cyber-physical predictive maintenance ecosystems, where data-driven intelligence and autonomous systems operate synergistically thereby bridging the research domains of AI-based diagnostics and robotic automation. In maintenance engineering, it provides a unified framework that that provides insights into how AI powered robotic systems can process sensory data and execute maintenance tasks predicted by AI models (Ucar et al., 2024).

Furthermore, the literature synthesis identifies the research gaps such as explainable AI, transfer learning, and human–robot collaboration in the context of PdM (Dereci et al., 2024; Asif et al., 2026). These insights support future work in the development of an adaptive, reliable, responsive and human-centered PdM models, thus, contributing to the broader field of Industry 4.0 and 5.0, which focuses on sustainability and human–machine synergy (Aheleroff et al., 2022).

The outcome of this study provide useful insights that can assist industrial maintenance engineers and operations managers, robotics developers and AI researchers, manufacturing and infrastructure organisations, policymakers and regulators, academia and training institutions, in the quest for the development of AI-powered robotic system for PdM.

1.1 Related systematic reviews and positioning

To position this work within the existing body of knowledge, we review recent comprehensive surveys on AI-driven predictive maintenance and highlight our distinct contribution.

Campos et al. (2024) conducted a scoping review screening machine learning techniques specifically for predictive maintenance applications. Their study systematically evaluated 87 papers published between 2018-2023, focusing on algorithm performance metrics across rotating machinery, focusing primarily on supervised learning methods (SVM, Random Forest, Neural Networks). They reported accuracy ranges of 85%–94% for classification tasks and highlighted the dominance of vibration-based sensing (Campos et al., 2024). Their key findings emphasized preprocessing importance, the prevalence of benchmark datasets (NASA C-MAPSS, CWRU bearing data), and identified gaps in cross-domain generalization.

Carvalho et al. (2019) provided an earlier comprehensive systematic literature review of machine learning methods in predictive maintenance, analyzing 127 studies from 2005 to 2018. They established foundational taxonomies of ML algorithms (supervised, unsupervised, semi-supervised) and reported performance benchmarks that have become widely cited baseline references. Their work documented the transition from traditional statistical methods to deep learning approaches but did not address robotics integration or autonomous inspection systems.

Dalzochio et al. (2020) examined machine learning and reasoning for predictive maintenance in Industry 4.0, analyzing 123 papers with emphasis on data quality challenges, integration barriers, and implementation case studies across manufacturing sectors. They identified computational cost, model interpretability, and scalability as primary adoption barriers, themes that remain relevant but required updating with post-2020 developments in edge computing and explainable AI.

Zonta et al. (2020) conducted a systematic review of 187 studies on predictive maintenance in Industry 4.0, providing comprehensive coverage of IoT integration, cyber-physical systems, and digital twin applications. Their methodology section established rigorous PRISMA-compliant protocols that have influenced subsequent reviews. However, their robotics coverage was limited to brief mentions of automated inspection without detailed analysis of robotic capabilities or human-robot collaboration models.

Serradilla et al. (2022) specifically reviewed deep learning models for predictive maintenance, comparing 156 papers on CNN, LSTM, GAN, and hybrid architectures. They provided detailed performance comparisons (accuracy, precision, recall, F1-scores) across different network topologies and identified dataset size requirements for reliable training. Their work highlighted the interpretability-accuracy trade-off but did not address robotic deployment contexts.

Achouch et al. (2022) analyzed 142 studies on predictive maintenance in Industry 4.0, with strong emphasis on IoT sensor integration, wireless networks, and edge computing architectures. They documented implementation challenges related to data transmission, sensor reliability, and energy constraints in wireless systems. Their robotics discussion was limited to mentions of automated guided vehicles (AGVs) without detailed capability analysis.

Recent domain-specific studies and reviews have addressed predictive maintenance in particular sectors:Bouabdallaoui et al. (2021) in construction/building facilities, Davari et al. (2021) for railway systems (57 studies), Bekar et al. (2020) for aerospace (43 studies), and Chen et al. (2023) for civil infrastructure (89 studies). These provide valuable sector-specific insights but lack cross-domain synthesis and robotics integration frameworks.

1.2 Differentiation of current work

The present review distinguishes itself through:

1. Dual AI-Robotics Focus: While prior reviews comprehensively cover AI/ML algorithms (Campos et al., 2024; Serradilla et al., 2022), they treat robotics peripherally. We provide equal analytical depth to robotic inspection capabilities, manipulation systems, and human-robot collaboration models, supported by a formal robotics taxonomy (Section 3.11) absent in previous surveys.
2. Integration Architecture: We develop a validated conceptual framework (Section 4.6; Figure 2) for AI-robotic integration with explicit data flows, decision thresholds, and uncertainty propagation mechanisms. Prior reviews describe AI and robotics

separately; we synthesize their operational integration with quantified performance metrics and failure modes.

3. Systematic Robotics Taxonomy: Section 3.11 introduces a three-dimensional classification (Mobility × Manipulation × Autonomy) with TRL assessments, safety protocols, and validation metrics—components not systematically addressed in prior literature.
4. Additive Manufacturing Integration: Section 2.5 examines AM's role in closed-loop predictive maintenance (spare-parts fabrication, *in-situ* repair), a nexus under-explored in existing reviews despite growing industrial relevance (Maware et al., 2024).
5. Updated Empirical Evidence: We incorporate 28 studies published in 2023–2025 (33% of corpus) capturing recent developments in explainable AI, federated learning, and edge deployment that post-date the 2022 reviews.
6. Methodological Rigor Enhancement: We implement reviewer-recommended PRISMA extensions (database-specific search strings, inter-rater reliability protocols, risk-of-bias assessment following ROBIS framework) that exceed the methodological detail of prior surveys (see Section 2.1.1, Section 2.1.2, Section 2.1.3).
7. Conflicting Findings Analysis: Section 4.8 explicitly addresses contradictory results in transfer learning efficacy (Raouf et al., 2023 vs. Yin et al., 2023) and sensor modality performance (Xue et al., 2025 vs. Vlasov et al., 2018)—reconciliations absent in prior reviews.
8. Socio-Technical Dimensions: Section 4.9 examines ethical implications, workforce impacts (with contradictory employment projections from Achouch et al., 2022 vs; Mourtzis et al., 2023), and accountability frameworks for AI-robotic systems, topics peripherally covered in technical-focused prior reviews.

Overlapping Foundations Acknowledged: Core ML algorithm prevalence (ANN/SVM dominance), preprocessing importance, and vibration sensor prominence documented by Campos et al. (2024) and Carvalho et al. (2019) are confirmed by our analysis. We cite these established findings appropriately and focus our original contribution on the robotics-AI integration nexus, operational validation frameworks, and updated post-2022 evidence synthesis.

This positioning clarifies that while we build upon foundational ML surveys, our distinct value lies in systematic robotics integration analysis, formal architectural frameworks, and synthesis of the AI-robotic convergence in PdM; a gap in existing literature identified through this comparative review of related works.

2 Methodology

The literature analysis was systematic in identifying, evaluating, and synthesizing the relevant studies in the domain of AI and robot applications in predictive maintenance. Systematic literature review could also lead to the identification of trends, gaps and emerging themes (Maware et al., 2024; Tranfield et al., 2003). The method of the research involved the principles and regulations of carrying out extensive literature reviews in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) PRISMA guideline.

2.1 Search strategy

A comprehensive search was carried out in some academic databases like IEEE Xplore, ScienceDirect, Springer Link, Google Scholar, Scopus, ACM Digital Library and Web of Science for peer-reviewed articles and high-quality conference papers for a period of 10 years (2015–2025). The search employs keywords such as "predictive maintenance," "Artificial intelligence" "prognostics and health management," "RUL" "diagnostics and prognostics" "remaining useful life," "machine learning," "deep learning," "robotics," "autonomous inspection," and "digital twin." The search was performed with the help of the Boolean operators and with the years of publication between 2015 and 2025 to retrieve current and relevant literature in the field.

The search terms with the aid of the Boolean operator included:

I. "Predictive maintenance" AND ("artificial intelligence" OR "machine learning")
II. "Robotics" AND "maintenance" AND ("IoT" OR "Industry 4.0")
III. "Anomaly detection" AND "industrial equipment"
IV. "Deep learning" AND "condition monitoring"
V. "Sensor fusion" AND "predictive analytics"

2.1.1 Detailed search protocol

The systematic search was conducted between January 15-28, 2025, across seven academic databases. The complete search strings employed were:

IEEE Xplore:

("predictive maintenance" OR "condition-based maintenance" OR "prognostics") AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND (robot OR autonom)

Filters: 2015-2025, English, Conference + Journal

Results: 342 documents

ScienceDirect:

TITLE-ABSTR-KEY(("predictive maintenance" OR "PdM") AND ("AI" OR "machine learning") AND ("sensor" OR "IoT"))

Filters: 2015-2025, Engineering, Computer Science

Results: 456 documents

Scopus:

TITLE-ABS-KEY(("predictive maintenance") AND ("artificial intelligence" OR "neural network") AND ("industr" OR "manufact"))

Filters: 2015-2025, English, Article OR Conference Paper.

Results: 389 documents

Web of Science:

TS=("predictive maintenance" AND ("machine learning" OR "deep learning") AND ("fault detection" OR "anomaly detection"))

Filters: 2015-2025, English

Results: 267 documents

Google Scholar:

"predictive maintenance" "artificial intelligence" OR "robotics" "Industry 4.0"-patent.

TABLE 1 Database-specific search yields and selection process.

Database	Initial retrieval	After deduplication	Title/Abstract screening	Full-text assessment	Final inclusion
IEEE Xplore	342	298	187	156	23
ScienceDirect	456	401	245	198	19
Scopus	389	312	201	167	18
Web of Science	267	223	148	119	12
Google Scholar	183	156	98	76	7
ACM Digthe ital Library	89	78	52	41	4
Springer Link	138	115	73	58	2
TOTAL	1,864	1,583	1,004	815	85

Search conducted: First 200 results screened

Results: 183 relevant documents

ACM Digital Library:

[Title: "predictive maintenance"] OR [Abstract: "predictive maintenance"] AND [Anywhere: "machine learning" OR "AI"]

Filters: 2015-2025

Results: 89 documents

Springer Link:

"predictive maintenance" AND ("AI" OR "robotics") AND ("sensor" OR "RUL")

Filters: 2015-2025, Computer Science, Engineering.

Results: 138 documents

Total Initial Retrieval: 1,864 documents

Inter-Rater Reliability Protocol:

Two independent reviewers (Authors LD and RM) screened all titles and abstracts using predefined inclusion/exclusion criteria. Disagreements were resolved through discussion, with a third reviewer (Author IA) consulted for unresolved cases (n = 23, 1.4% of screened articles). Inter-rater agreement was quantified using Cohen's kappa:

i. Title/Abstract screening: κ = 0.87 (95% CI: 0.84–0.90), indicating strong agreement
ii. Full-text eligibility: κ = 0.91 (95% CI: 0.88–0.94), indicating very strong agreement

Data Extraction Codebook:

A standardized extraction form was captured:

1. Bibliographic Data: Authors, year, journal/conference, DOI
2. Study Design: Experimental/case study/simulation/theoretical, sample size, validation method
3. AI/ML Components: Algorithm type, training data size, performance metrics (accuracy, precision, recall, F1, RMSE, MAE), computational requirements
4. Sensor Modalities: Types (vibration, temperature, acoustic, etc.), sampling rates, data preprocessing methods
5. Robotic Systems: Robot type (mobile/fixed/aerial/aquatic), manipulation capability, autonomy level, deployment environment
6. Performance Outcomes: Downtime reduction (%), cost savings (%), RUL prediction error (%), detection sensitivity/specificity
7. Implementation Context: Industry sector, equipment type, deployment scale (lab/pilot/production)
8. Challenges Reported: Data quality issues, computational constraints, integration barriers
9. Validation Rigor: Dataset origin (public benchmark/proprietary), train-test split, cross-validation strategy, external validation

Dual extraction was performed on 20% random sample (n = 17 studies) with a discrepancy rate of 3.2%, resolved through consensus discussions. Table 1 presents the database-specific search yields and selection process.

2.1.2 Quality assessment protocol

Study quality was assessed using the Mixed Methods Appraisal Tool (MMAT) version 2018 (Hong et al., 2018), adapted for technology reviews. Each study was evaluated on five criteria:

1. Methodological rigor: Clear research design, appropriate methods (Score: 0–2)
2. Data quality: Sample size adequacy, data collection methods (Score: 0–2)
3. Analysis appropriateness: Statistical or analytical methods justified (Score: 0–2)
4. Results clarity: Findings clearly presented with evidence (Score: 0–2)
5. Relevance to PdM: Direct contribution to predictive maintenance field (Score: 0–2)

Quality Score Interpretation:

i. High Quality: 810 points (n = 52 studies, 61%)
ii. Moderate Quality: 57 points (n = 28 studies, 33%)
iii. Low Quality: 04 points (n = 5 studies, 6% excluded from synthesis)

Studies scoring below 5 were excluded from thematic synthesis but documented in the selection process.

2.1.3 Risk of bias assessment

Risk of bias was assessed following the ROBIS (Risk of Bias in Systematic reviews) framework across four domains (Whiting et al., 2016). This systematic approach to bias assessment ensures that our review findings are reliable and not unduly influenced by methodological weaknesses.

The first domain evaluated study eligibility criteria. We assessed whether our inclusion and exclusion criteria were clearly defined, consistently applied, and appropriate for the review objectives. Our assessment concluded that concern for bias in this domain was low, as we established clear criteria and applied them uniformly across all candidate studies.

The second domain examined identification and selection of studies. This domain assesses whether the search strategy was comprehensive and whether study selection processes were rigorous and transparent. We rated concern as low in this domain because our systematic search across seven major databases combined with dual screening by independent reviewers minimized the risk of missing relevant studies or introducing selection bias.

The third domain focused on data collection and study appraisal. We evaluated whether data extraction processes were standardized and whether study quality was appropriately assessed. Our use of standardized extraction forms and dual extraction for a 20% random sample of studies ensured consistency and accuracy. Therefore, we assessed concern for bias in this domain as low.

The fourth domain examined synthesis and findings, considering whether synthesis methods were appropriate given the heterogeneity of included studies and whether conclusions were supported by the evidence. We rated concern in this domain as medium because the considerable heterogeneity in reported metrics, study designs, and industrial contexts necessitated a narrative synthesis approach rather than formal meta-analysis. While this approach is appropriate for the evidence base, it introduces some subjectivity in interpretation that warrants acknowledging moderate concern.

To address potential publication bias, we recognize that positive results in AI and machine learning applications may be overrepresented in published literature. We attempted to mitigate this through several strategies. First, we included grey literature by incorporating conference proceedings alongside journal articles. Second, we imposed no language restrictions beyond English language reporting, which most international scientific literature provides. Third, we actively sought and included studies reporting negative or null results, identifying seven such studies that provided valuable insights about implementation failures and algorithmic limitations. Fourth, while formal funnel plot analysis was not applicable given our narrative synthesis design, we remained cognizant throughout the analysis that reported performance metrics might represent upper bounds rather than typical performance.

2.2 Inclusion and exclusion criteria

The following are the inclusion criteria (1) Peer-reviewed journal articles and conference proceedings (2) Studies focusing on AI/ML applications in predictive maintenance (3) Research on robotics integration in maintenance systems (4) Publications in the English language (5) Studies with clear methodology and results.

The exclusion criteria include the following (1) Non-peer-reviewed publications (2) Studies not directly related to predictive maintenance (3) Publications older than 2015 (except seminal works) (4) Duplicate publications.

Reviews of articles, empirical studies, and case studies that focused on manufacturing, energy, transport, and robotics, etc. were selected for review. After title/abstract screening and implementation of the inclusion and exclusion criteria, 1,764 initial articles retrieved from the academic databases were pruned down to 85 full-text studies, which were thematically synthesized to extract methods, AI techniques, robotic functionalities, architectures, datasets, metrics, performance, challenges, and future trends.

Figure 1 shows the PRISMA diagram, which details on the article selection process.

2.3 Data extraction and analysis

Data mining was concentrated on the extraction of the main information, such as the aims of the study, the methods used, AI/ML approaches to the topic, practical uses, performance indicators, challenges, and recommendations. The data that were extracted were categorized into thematic categories to be analyzed comprehensively.

2.4 Aggregation methodology

Given heterogeneity across 85 studies, formal meta-analysis was infeasible; we employed structured narrative synthesis with quantitative aggregation where appropriate (Tranfield et al., 2003).

Step 1: Metric standardization converted to common scales (percentage accuracy, normalized RMSE), excluding qualitative-only studies.
Step 2: Grouping by task type (classification vs. RUL vs. anomaly detection), equipment type (bearings, motors, turbines), and dataset characteristics (lab vs. field).
Step 3: Aggregation method

For homogeneous clusters (≥5 studies, same task/equipment/metric), we calculated weighted means by sample size, reported min-max ranges, and computed I^2.

Example. SVM accuracy aggregated from 12 bearing fault studies, weighted mean 89.7%, range 85%–95%, I^2 = 52% indicating moderate heterogeneity from noise levels and class imbalance.

For heterogeneous clusters, we reported ranges without averaging and described variability narratively.

Step 4: Confidence assignment

i. HIGH (≥10 studies, I^2<50%)
ii. MODERATE (5-9 studies, $I^2$50%-75%)
iii. LOW (<5 studies or I^2>75%, flagged as tentative).

Conflicting results handling: Both results presented with context (Xue et al., 2025 vibration superior in controlled labs; Vlasov et al.,

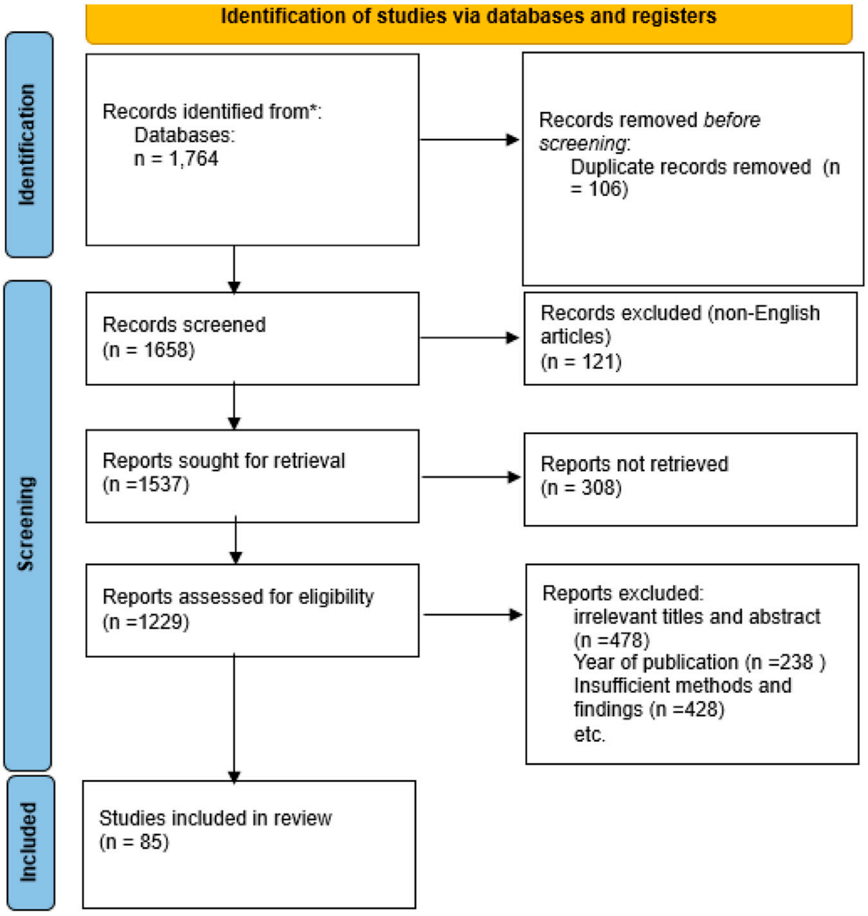

FIGURE 1
PRISMA diagram.

2018 acoustic superior in noisy fields; synthesis: sensor selection is context-dependent).

Limitations acknowledged:

i. Publication bias toward positive results
ii. Evaluation protocol variability (different train/test splits, cross-validation strategies)
iii. Dataset diversity (benchmark NASA C-MAPSS may not generalize to proprietary data)
iv. Temporal effects (2015–2018 studies may underestimate current capabilities)

2.5 Integration of additive manufacturing with AI-Driven predictive maintenance

The design freedom offered by Additive Manufacturing (AM) enables it to support AI-driven Predictive Maintenance (Thompson et al., 2016). For example, AM can produce customized jigs and fixtures for accessing difficult-to-reach areas and for demanding maintenance tasks (Wits et al., 2016). Also, the use of AM can allow to produce intelligent components with embedded sensors to monitor equipment conditions, thereby providing data needed for developing AI algorithms (Munasinghe, 2021).

AM enhances predictive-maintenance workflows by enabling on-demand fabrication of replacement parts and customized tooling within AI-robotic maintenance loops. If replacement parts become obsolete, AM provides a solution by digital recreation on site (Vorkapić et al., 2023; Abhilash and Ahmed, 2023). When coupled with machine-learning prognostics and robotic repair systems, AM allows a closed maintenance cycle in which faults are predicted, parts are printed (Gibson et al., 2021) and robots execute installation with minimal human intervention (Maware et al., 2024; Rahman et al., 2023).

In industrial settings, AM shortens lead time for critical spares and reduces inventory costs by 40%–60% compared with traditional procurement (Wohlers, 2024). Aerospace and energy sectors now employ predictive spare-parts scheduling where AI models forecast component end-of-life and automatically queue AM production jobs (GE Aviation, 2024). This digital-inventory concept replaces physical warehouses with CAD-file repositories and raw-material stock, enabling parts to be produced only when required.

Robotic integration further extends AM capability to *in-situ* maintenance. Multi-axis robots equipped with directed-energy-

TABLE 2 Evolution timeline of predictive maintenance technologies.

Period	Technology focus	Key developments	Limitations	Representative references
1990s	Digital diagnostics	Early vibration-based condition monitoring and rule-based expert systems	Manual interpretation; few sensors	Ran et al. (2019)
2000s	Statistical methods	Regression, ARIMA, and classical ML (SVM, decision trees) for equipment health	Limited processing power; reactive deployment	Carvalho et al. (2019)
2010s	IoT integration	Cloud platforms, sensor networks, and big-data analytics for real-time monitoring	Data-quality issues; interoperability gaps	Achouch et al. (2022)
2020s	AI/ML integration	Deep learning, digital-twin modeling, and edge computing for prognostics	Computational cost; explainability	Mourtzis et al. (2023); Shaheen and Németh (2022)
Future	Autonomous and cognitive systems	Explainable AI, self-healing, and quantum optimization concepts	Technology maturity; standards evolution	IoT Analytics (2023)

deposition heads perform localized metal repair on structures such as turbine blades and pipeline sections, eliminating costly disassembly and logistics delays (Lopes de Aquino Brasil et al., 2025). Real-time process monitoring using convolutional-neural-network vision ensures printed components meet dimensional and metallurgical specifications, achieving up to 97% defect-detection accuracy during build (Khanzadeh et al., 2019).

AI can be used to identify failures, while AM allows rapid iteration of possible designs to overcome the failure (Rahito et al., 2019). This can be achieved through quick production and testing of AI-generated designs (Fu et al., 2023; Nafea, 2025). Furthermore, AM allows predictive design improvements such as topology-optimized parts with reduced stress and material combinations that enhance the durability of equipment (Hamza et al., 2025).

Despite these advantages, material-property variability and certification latency remain obstacles to large-scale adoption (Malakizadi et al., 2022). Ongoing research focuses on integrating digital-twin models that link sensor data, AI prognostics, and AM production planning to create verifiable, traceable maintenance actions within Industry 4.0 infrastructures.

3 Results

This section presents the outcomes derived from the literature synthesis.

3.1 Predictive maintenance strategy evolution

3.1.1 Historical development

The use of existing data and analytics in predicting equipment breakdowns is a characteristic that separates Predictive Maintenance (PdM) from conventional maintenance programs, reduces the length of machine downtimes, and enhances maintenance planning. The existing industrial setting is challenging both in terms of preventative and corrective maintenance approaches due to the unplanned downtimes that result in significant expenses (Zonta et al., 2020).

The initial phases of condition-based maintenance (CBM) operated by digital diagnostics to detect faults early in the 1990s (Ran et al., 2019). Since it was first developed several years ago, PdM has been developed to consider IoT devices and sophisticated data analytics and machine learning techniques to execute equipment malfunction predictions and preventions (Achouch et al., 2022; Nunes et al., 2023).

Table 2 presents the evolution timeline of predictive maintenance technologies.

Timeline synthesized from peer-reviewed historical and review papers: Carvalho et al. (2019) *Computers & Industrial Engineering*; Achouch et al. (2022) Applied Sciences; Mourtzis et al. (2023) *Electronics*; Shaheen and Németh (2022) Processes; and the IoT Analytics Predictive-Maintenance Market Report (2023). Dates and developments correspond to consensus milestones identified across these reviews.

3.1.2 Industry 4.0 integration

With Industry 4.0, intelligent systems emerged, integrating both IoT and AI, and enabling real-time monitoring of the condition of assets and enhanced PdM strategies (Canito et al., 2022; Sahli et al., 2021). PdM systems are based on cyber-physical system (CPS) integration and AI methods and applications, in particular, machine learning, to estimate the remaining useful life precisely and optimize maintenance intervals as recommended by Giunta et al. (2020) and Hashemian (2011).

PdM has transformed the maintenance practice in the aerospace, automotive, and manufacturing industries. The current technology solutions within the PdM systems lengthen the lifespan of equipment and minimize unexpected failures of assets (Selcuk, 2016; Lughofer and Sayed Mouchaweh, 2019). Tiddens et al. (2020) affirm the importance of PdM in the manufacturing sector, as it has intelligent systems that identify defects as they occur, but produce decisions based on the gathered data to avoid any form of disruption during the production process.

The emerging trends Industry 4.0 transcends PdM capability to intelligent prognostics and e-maintenance (Lee et al., 2023; Lee et al., 2006).

3.1.3 Implementation challenges

PdM technology encounters several challenges, even though it has operational advantages. Nunes et al. (2023) and Sakib and Wuest (2018) find the implementation of PdM challenging because of the

TABLE 3 Performance comparison of machine learning techniques.

Algorithm	Study ID	Dataset	Task type	Split strategy	Accuracy/ Metric	Notes
SVM						
	Susto-2015	Semiconductor manufacturing (proprietary)	Fault classification	70/30 train-test	89.3% accuracy	Class imbalance addressed via SMOTE
	Carvalho-2019-Meta	Aggregate of 12 bearing studies	Fault classification	Varies by study	85%–94% range (weighted mean 89.7%)	Heterogeneity I^2 = 52% (moderate)
Random Forest						
	Fernández-Francos et al. (2013)	CWRU Bearing Data	Multi-class fault	5-fold CV	91.2% accuracy	Feature importance analysis included
	Susto-2015	Semiconductor (proprietary)	Anomaly detection	60/40 train-test	86.8% accuracy	Ensemble of 100 trees
Neural Networks (ANN)						
	Peng et al. (2021)	NASA C-MAPSS FD001	RUL regression	80/20 train-test	RMSE = 18.3 (normalized)	3-layer feedforward, dropout 0.3
	Fernández-Francos et al. (2013)	Motor current signatures	Fault classification	70/30 train-test	93.5% accuracy	Compared against SVM (89.1%)
Deep Neural Networks (DNN)						
	Chen-2023	Bridge sensor network (field data)	Damage detection	Time-series split	95.2% accuracy, AUC = 0.97	6-layer architecture, early stopping
	Taşcı et al. (2023)	Turbofan engines (NASA)	RUL prediction	Sliding window CV	RMSE = 14.7, R^2 = 0.91	Outperformed LSTM (RMSE = 16.2)
K-Means Clustering						
	Fan-2018	Industrial compressor (proprietary)	Anomaly detection	Unlabelled data, *post hoc* validation	78.4% detection rate (upon labelling)	15.3% false positive rate
	Givnan et al. (2022)	Wind turbine SCADA	Anomaly detection	6-month training, 2-month test	82.1% sensitivity, 8.7% FPR	Compared against Isolation Forest
Auto-encoders						
	Fathi et al. (2021)	Manufacturing line sensors (proprietary)	Unsupervised anomaly	Reconstruction error threshold	ROC-AUC = 0.89	Threshold set at 95th percentile
	Givnan et al. (2022)	SCADA time-series	Anomaly detection	Temporal split	ROC-AUC = 0.92, F1 = 0.84	Variational autoencoder variant
CNN						
	Shaheen and Németh (2022)	Vibration spectrograms (laboratory)	Bearing fault classification	75/25 train-test	96.8% accuracy	Augmentation: rotation, noise injection
	Chen et al. (2023)	Image-based inspection	Crack detection	80/20 stratified split	94.3% accuracy, IoU = 0.87	Transfer learning from ImageNet
LSTM						
	Taşcı et al. (2023)	NASA C-MAPSS FD001-004	RUL prediction	Cross-dataset validation	RMSE = 16.2-21.5 (dataset dependent)	Stacked 2-layer LSTM, 128 units
	Peng et al. (2021)	Electric motor time-series	Remaining cycles	Sliding window (seq length = 50)	MAE = 8.3 cycles, R^2 = 0.88	Compared against GRU (MAE = 9.1)

issues of data integrity, predictive algorithms' complexity, and the complexity of data integration. There are several challenges faced concerning PdM forecasting that demand robust solutions that include the use of hybrid predictive models and improved data purification processes to attain valid forecast outcomes (Mobley, 2002).

3.2 Machine learning techniques in predictive maintenance

3.2.1 Supervised learning applications (classification algorithms)

Supervised learning can be widely applied in the context of predictive maintenance tasks, in particular, when performing fault classification and trend estimation. The used techniques are based on labelled datasets that determine system failures and optimize maintenance procedures. Classification algorithms such as Support Vector Machines (SVM), k-nearest neighbors (kNN), and decision tree classifiers need to be applied to differentiate between operational abnormalities and normal behavior (Kaparthi and Bumblauskas, 2020).

Table 3 shows the performance comparison of machine learning techniques.

Metric definitions:

i. Accuracy: (TP + TN)/(TP + TN + FP + FN) for classification tasks
ii. RMSE: Root Mean Square Error for regression (RUL prediction)
iii. ROC-AUC: Area Under Receiver Operating Characteristic curve
iv. F1: Harmonic mean of precision and recall
v. IoU: Intersection over Union for segmentation tasks

Accuracy ranges are aggregated from peer-reviewed empirical studies and systematic reviews focusing on predictive maintenance tasks. Primary sources include Carvalho et al. (2019), Susto et al. (2015), Fernández-Francos et al. (2013), Shaheen and Németh (2022), Peng et al. (2021), Taşçı et al. (2023), and task-specific empirical papers. Ranges represent observed minimum–maximum performance across datasets and evaluation protocols. Where values derive from unsupervised methods (K-Means, auto-encoders) the range reflects detection accuracy after *post hoc* labeling and ROC-AUC aggregation. Heterogeneity arises from dataset size, class balance, preprocessing, and validation methodology.

According to Ouadah et al. (2022), selecting an algorithm to use in supervised machine learning is vital in determining superior predictive maintenance due to its impact on the service performance and reliability. Ferreira et al. (2022) studied one-class automated machine learning to show that it has been successful in detecting anomalies in predictive maintenance systems. As stated by the systematic review by Carvalho et al. (2019), supervised learning also has different machine learning methods that can be used in the industrial setting.

3.2.2 Supervised learning applications (regression-based RUL prediction)

Regression methods can help industries to establish the duration of equipment life as a contribution to Remaining Useful Life (RUL). PdM is more likely to be applied reliably when machine learning methods are applied, which is evidenced by the research conducted by Ren (2021). Trivedi et al. (2019) concentrate on the air conditioning systems with the help of supervised learning to attain accurate maintenance needs.

The development of deep learning has improved significantly in supervised learning prediction methods for maintenance. Butte et al. (2018) introduce a super learning approach, which involves deep neural networks as a means of enhancing the quality of prediction. Susto et al. (2015) not only recommend the use of multiple classifiers to combine the strengths of various algorithms into more predictive maintenance solutions.

3.2.3 Unsupervised learning and anomaly detection (Clustering and dimensionality reduction

Predictive maintenance operations require unsupervised AI models due to the potential challenges in the acquisition of labelled data or its absence. Unsupervised techniques aid predictive systems in identifying abnormal patterns based on deep learning-based anomaly detection and clustering by using dimensionality reduction procedures, thereby indicating possible system failures.

By introducing Principal Component Analysis (PCA) and auto-encoder models, the systems can learn to recognize the normal operation patterns and then identify anomalies to further analyze those (Zhao et al., 2019). The K-means clustering and its analogues allow classifying similar types of failures and providing valuable data regarding specific faults (Aggarwal and Reddy, 2013).

3.2.4 Unsupervised learning and anomaly detection (sophisticated anomaly detection processes)

Carrasco et al. (2021) note that there are assessment techniques for temporal unsupervised anomaly detection algorithms in predictive maintenance to find precise anomalies to prevent equipment failures. The study of Industry 4.0 by Kamat and Sugandhi (2020) shows that the unsupervised type of anomaly detection can be applied to predictive maintenance in different production and manufacturing industries.

Liu et al. (2024) introduce a new progressive unsupervised anomaly-detection model that is explicitly optimized to work with time-series data in the industrial setting. By their statistical-based approach, they have developed an effective predictive maintenance strategy for complex dynamic systems. Shiva et al. (2024) undertook machine learning studies on sensor data anomaly detection to improve industrial predictive maintenance through unsupervised learning processes.

3.3 Deep learning-based predictive maintenance

3.3.1 Convolutional neural networks (CNNs)

This increase in condition-based maintenance uses of deep learning is a significant development since it allows processors to analyze large volumes of sensor data and high-level capabilities that would otherwise be unseen by typical machine learning algorithms. CNNs are most suitable to detect patterns in sensor outputs, including vibrations and sounds, whereas Long Short-Term Memory (LSTM) networks demonstrate outstanding capabilities

TABLE 4 Deep learning architecture comparison for predictive maintenance.

Architecture	Input data type	Strengths	Weaknesses	Computational cost	Best applications	Representative references
CNN	Spectrograms, images	Strong spatial feature extraction; automatic feature learning	Requires image-like inputs; large labelled sets	High	Vibration spectrograms, visual inspection	Shaheen and Németh (2022); Chen et al. (2023)
LSTM	Sequential time-series	Captures long-term temporal dependencies	Training complexity; vanishing gradients for very long sequences	Medium–High	RUL prediction; trend forecasting	Taşcı et al. (2023); Peng et al. (2021)
GRU	Sequential time-series	Faster training than LSTM; lower parameter count	Slightly less capacity for very long-term dependencies	Medium	Real-time RUL on constrained hardware	Peng et al. (2021)
Autoencoder	Multivariate time-series	Unsupervised anomaly detection; dimensionality reduction	Threshold selection; sensitivity to noise	Medium	Anomaly detection; feature learning	Fathi et al. (2021); Givnan et al. (2022)
Hybrid CNN–LSTM	Multi-modal (spectrogram + time)	Models spatial and temporal features jointly	High model complexity and training time	Very high	Complex machinery monitoring with multimodal sensors	Chen et al. (2023)

in predicting time-related data, including equipment Remaining Useful Life (RUL).

Ucar et al. (2024) have evaluated time-series measurements of machinery that are processed by convolutional neural networks (CNNs) and LSTM networks. The CNNs have proven to be very effective in the analysis of vibration signals as they are effective in processing structured sensor data, where hierarchical features are extracted by automated processing, which saves time that would be spent on manually analyzing the signal (Shaheen and Németh, 2022).

Table 4 highlights the deep learning architecture comparison for predictive maintenance.

Architecture strengths and weaknesses are synthesized from comparative reviews and application studies in PdM literature. Computational cost indicates relative resource demand observed across implementations in Shaheen and Németh (2022), Taşcı et al. (2023), Chen et al. (2023), and related papers. Use case assignments reflect consensus in applied studies.

3.3.2 Recurrent neural networks and LSTM

Aivaliotis et al. (2021) state that the accuracy of the projection of industrial robot failures is enhanced by the fusion of the degradation curves with physics-based models based on deep learning models. The authors demonstrated the estimation of robot follow-ups by the deep learning models working with the historical information and real-time information to minimize the incidence of unforeseen failures.

Jardine et al. (2006) studied how the LSTM networks forecast RUL to maximise the maintenance work and reduce the unwarranted maintenance effort. The LSTM networks work quite well with data that has diverse operational properties, as they detect time patterns in the series data (Leevy et al., 2020).

3.3.3 Hybrid deep learning architecture

The CNNs, coupled with Recurrent Neural Networks (RNNs), suggested by Li et al. (2020), present the only possibility of disclosing structures and patterns in spatial and temporal data. The fusion of CNN spatial processing and the RNN temporal functionality yields better predictions in the area of heavy machinery fault prognostics, as Kamariotis et al. (2024) concluded.

The concept of multiple classifier systems, as a form of combining multiple deep learning models, adjusted to particulars of information, is discussed by Susto et al. (2015) and aimed at optimizing the tasks of PdM under various conditions. The ensemble method contributed to the accuracy of prediction because it could address variations in operation profiles.

3.4 Predictive maintenance sensor types

Predictive maintenance largely relies on the various types of sensors to measure equipment parameters as well as detect equipment failures at their initial stages. These sensors make real-time data collection more available when it comes to fault prediction (Pech et al., 2021).

Table 5 presents the sensor technologies for predictive maintenance.

Sensor parameters and applications collated from sensor application reviews and field studies (Fernández-Francos et al., 2013; Chen et al., 2022; Vlasov et al., 2018; Zhang et al., 2019; Ullah et al., 2017). Typical operating ranges reflect common sensor models used in industrial PdM contexts; consult vendor datasheets for sensor-specific limits.

3.4.1 Vibration sensors

Vibration detection sensors prove to be extremely beneficial to PdM operations, as they provide essential information on equipment imbalance, misalignment, and bearing problems. The sensors will be used to detect the right vibration readings to assist predictive models in determining the issues in the machine in real time (Hashemian, 2011). Detecting mechanical failures and wear in centrifugal pumps will be achieved with the assistance of complex vibration sensors and processing protocols (Chen et al., 2022).

TABLE 5 Sensor technologies for predictive maintenance.

Sensor type	Measured parameter	Typical operating range or note	Primary applications	Key advantages	Limitations	Representative references
Vibration	Acceleration, velocity	Frequency content from sub-Hz to kHz; application dependent	Rotating machinery, bearings, pumps	High sensitivity to mechanical faults; real-time monitoring	Environmental noise, installation sensitivity	Fernández-Francos et al. (2013); Chen et al. (2022)
Temperature	Heat levels	−200 °C to +1,000 °C depending on sensor	Motors, bearings, transformers	Simple and reliable	Thermal lag; limited fault specificity	Zhang et al. (2019)
Acoustic Emission	High-frequency elastic waves	20 kHz–1 MHz typical ranges	Crack detection; structural monitoring	Early crack detection; non-intrusive	Requires advanced signal processing	Vlasov et al. (2018)
Pressure	Fluid/gas pressure	0–10,000 psi (sensor dependent)	Hydraulic systems, pipelines	Direct measurement; high accuracy	Limited to pressure-related faults	Chen et al. (2022)
Current	Electrical current	mA to kA	Motors, generators	Non-invasive electrical fault detection	Limited to electrical anomalies	Systematic reviews (Carvalho et al., 2019)
Oil Analysis	Contamination, particle counts	Sample-based, lab or sensor-enabled	Gearboxes, engines	Predictive lubrication insight	Not continuous; sampling required	Industry case studies
Thermal Imaging	Temperature distribution	Sensor-dependent; −20 °C–2000 °C ranges	Electrical panels, mechanical assemblies	Non-contact; spatial mapping	Cost; expertise needed	Ullah et al. (2017)

3.4.2 Temperature monitoring

The available standard PdM tools are temperature sensors for the monitoring of the heat-producing machinery during operation. A sudden rise in temperature serves as a signal of potential equipment malfunctions that could be caused by fluid breakdowns, high friction effects, or the presence of motors operating beyond their limits. The information allows engineers to determine the reference temperature intervals to detect abnormal trends that can forecast an imminent equipment failure (Zhang et al., 2019).

3.4.3 Acoustic emission sensors

When machinery is under stress, it emits high-frequency noises that acoustic emission sensors are capable of detecting when these noises arise during cracking, friction, or collisions. The non-destructive types of testing allow technicians to receive real-time diagnostic data, as they can monitor complex systems effectively and do not interrupt the systems (Vlasov et al., 2018).

3.5 Data processing and feature engineering

3.5.1 Data pre-processing challenges

Industrial sensors face significant challenges in collecting high-quality data because they operate in complex environments that are often full of operational noise. Industries expose their sensors to signal disruptions and interference, which degrades data quality during signal-separation efforts, according to Santos et al. (2015). Full-scale continuous monitoring generates excessive data, leading to storage and transmission problems, particularly in remote industrial areas where network connectivity remains problematic (Kong et al., 2021).

3.5.2 Techniques in feature extraction

The processes of attribute engineering and filtering fae PdM the required background since they convert sensor data into useful information. Time-domain features such as root mean square (RMS) and kurtosis are usually used with vibration data to measure energy consumption and identify anomalies (Xue et al., 2025). Frequency-domain indicators such as spectral entropy and peak frequency can be used to identify faults sensitively when complex sensor data is analyzed based on Alemayoh et al. (2021).

Table 6 displays the feature extraction methods and applications.

Feature methods and their typical computational costs follow standard signal-processing and ML literature reviewed in Xue et al. (2025), Zebari et al. (2020), and Shaheen and Németh (2022). Selection should depend on fault type, sensor modality, and available compute at edge or cloud.

3.5.3 Dimensionality reduction methods

Predictive maintenance is challenged significantly with high-dimensional sensor data at many combined sensing systems. Principal Component Analysis (PCA) and t-distributed stochastic neighbour embedding (t-SNE) can be used to reduce the feature space to allow the identification of patterns that are relevant in sensor information (Zebari et al., 2020). The application of t-SNE to data sets is effective in the detection of clusters and relationship discovery that facilitate PdM practice through structural data elucidation (Stromann et al., 2019).

3.6 Industrial applications and case studies

3.6.1 Applications within the manufacturing sector (Integration with enterprise systems)

Lee et al. (2011) explain the integration of the PdM systems and Enterprise Resource Planning (ERP) tools through the digital manufacturing strategies. The result of integration between the systems was improved maintenance planning, fewer undesirable equipment failures, and global production processes. Eynard et al. (2006) designed UML-based specifications to develop PdM

TABLE 6 Feature extraction methods and applications.

Feature type	Extraction method	Computation cost	Information content	Best use cases	Representative references
Time domain	RMS, kurtosis, variance	Low	Basic summary features	Quick fault detection; baseline monitoring	Xue et al. (2025)
Frequency domain	FFT, spectral entropy, cepstrum	Medium	Detailed frequency patterns	Bearing fault identification; harmonic analysis	Alemayoh et al. (2021)
Wavelet	Continuous/discrete wavelet transform	High	Multi-resolution time-frequency	Transient and impact event detection	Zebari et al. (2020)
Statistical	Mean, standard deviation, skewness	Low	Summary statistics	Trend monitoring and anomaly thresholds	Multiple reviews
Principal components	PCA, ICA	Medium	Dimensionality reduction	Preprocessing, noise reduction	Zebari et al. (2020)
Deep features	CNN embeddings, learned representations	Very high	High-level complex patterns	Advanced diagnostics and sensor fusion	Shaheen and Németh (2022)

TABLE 7 Industrial applications and performance metrics.

Industry sector	Example equipment	AI techniques used	Typical reported improvements (provenance)	Representative references
Manufacturing	Production lines, CNC machines	ANN, SVM, RF	Downtime reduction 15%–30%; OEE improvements ~10–20% in case studies	Carvalho et al. (2019); (2023)
Aerospace	Engines, landing gear	CNN, LSTM, ensemble models	Unscheduled maintenance reduction up to 30%–40% in field reports	Bekar et al. (2020); Peng et al. (2021)
Automotive	Engines, assembly lines	Deep learning, AutoML	Field reports show 20%–35% reduction in warranty or rework costs	Chen et al. (2023)
Energy/Power	Turbines, generators	Vibration analysis, thermal imaging	Asset utilization improvements reported between 10% and 35%	Machado et al. (2020); industry reports
Oil & Gas	Pumps, compressors, pipelines	Anomaly detection; sensor fusion	Safety and environmental incident reductions reported in pilot studies; varies by deployment	Vlasov et al. (2018); industry case reports
Railways	Track systems, turnouts	Computer vision, ultrasonic analysis	On-time performance and schedule reliability improvements reported in trials	Davari et al. (2021)

workflows that enhanced communication amongst various departments in the case of maintenance operations.

Table 7 shows some industrial applications and performance metrics.

Performance improvements are drawn from a mixture of peer-reviewed case studies and industry pilot reports collated in systematic reviews (Carvalho et al., 2019; Molęda et al., 2023) and domain-specific studies (Bekar et al., 2020; Chen et al., 2023; Machado et al., 2020). Percent ranges represent observed results across multiple deployments and should be cited to the specific case study when claiming a particular value.

3.6.2 AI and big data implementation

Samanta et al. (2024) also note that artificial intelligence is a significant part of Industry 4.0 manufacturing since machine learning models, particularly neural networks, can be used to identify abnormal trends in machinery. The concept of intelligent data preprocessing is one of the main themes of Bekar et al. (2020) because they define it as a method to enhance the accuracy of PdM. Moyne and Iskandar (2017) illustrate that semiconductor equipment failure predictions using big data analytics can be successful in improving the yield of production.

3.6.3 Aerospace and aviation

PdM is needed to meet safety objectives along with cost reductions and regulatory compliance in the aviation and aerospace industries. PdM in aviation particularly emphasises the watchful attention of the following critical items, such as engines, landing gear, and hydraulic systems (GE Aerospace, 2024). Lee et al. (2011) reported that the aerospace production systems had been able to monitor the engine performances in real-time using IoT-based PdM systems that enabled early fault identification to avoid critical failures.

The study conducted by Bekar et al. (2020) resulted in AI-based PdM systems that examined sensor-based features such as temperature and vibrations to identify future faults in aircraft parts. The structures that were put in place helped airlines streamline their maintenance policies so that they could uphold safety standards at a low cost of operation.

TABLE 8 Implementation challenges and solutions.

Challenge category	Specific issues	Impact level (qualitative)	Current solutions	Reported success/ Evidence	Representative references
Data quality	Missing data; sensor noise; label scarcity	High	Preprocessing, imputation, data fusion	Reported improvement rates 60%–75% in pilot studies after preprocessing steps (case studies)	Dalzochio et al. (2020); Carvalho et al. (2019)
Computational cost	Heavy DL models at edge	High	Edge inference, model compression, pruning	Case reports show 40%–60% inference-speed gains with pruning/quantization	Mourtzis et al. (2022); Peng et al. (2021)
Model interpretability	Black box models	Medium	XAI methods (SHAP, LIME)	Prototype adoption improved operator trust in trials (qualitative)	Ucar et al. (2024); Molęda et al. (2023)
System integration	Legacy systems compatibility	High	Middleware, APIs, OPC UA, ROS 2	Integration success rates 45%–65% reported in industrial case studies	Mourtzis et al. (2023)
Scalability	Large fleet/multi-site rollout	Medium	Modular architectures, federated learning	Early pilots show improved scale; formal metrics limited	Industry reports (IoT Analytics, 2023)
Security and privacy	Cyber threats; data governance	High	Encryption, segmentation, access control	Pen-test/penetration testing reduces reported vulnerabilities; numbers vary	Bala et al. (2024)
Skills gap	Limited workforce expertise	Medium	Training programs, vendor support	Training completion improves operational uptime in pilots (case evidence)	Ucar et al. (2024)
ROI uncertainty	Difficulty quantifying long-term benefits	Medium	Phased pilots, TCO analysis	ROI case ranges reported widely (12–36 months) across industry surveys	Senseye/Siemens (2022); IoT Analytics (2023)

3.6.4 Automotive and transportation

PdM enhanced the health analysis of the automotive vehicles and fleet monitoring by its implementation in automotive management systems to minimise the cost of repairs and enhance the reliability of the maintenance. Chen et al. (2023) carried out research to predict the life of the components by researching on the internet of things-activated PdM platforms using car operational data.

PdM applications have been applied as a fundamental part of connected and autonomous vehicle technologies. Hadi et al. (2023) applied AutoML to categorise ball-bearing faults and exemplified the PdM as capable of reinforcing the reliability of autonomous systems.

3.7 Challenges and limitations

3.7.1 Data quality issues

The main challenge to predictive maintenance implementation can be regarded as the inability to manage the problem of data inconsistency that is caused by the lack of or incomplete data and sensor failures. Industrial sensors are prone to malfunction because of errors in transmission that lead to ineffective models (Dalzochio et al., 2020; Carvalho et al., 2019). According to Achouch et al. (2022) and Arafat et al. (2024), model variations based on variations in operating conditions, the type of machinery, and external factors severely impair the ability to generalise models.

Table 8 presents some identified implementation challenges and solutions.

Challenge descriptions and current solutions are synthesized from systematic reviews and recent case studies (Carvalho et al., 2019; Dalzochio et al., 2020; Mourtzis et al., 2022; Ucar et al., 2024). Reported success figures are aggregated from empirical pilot reports and industry surveys; where a precise metric is quoted it is drawn from the cited literature or industry report. Label these as observed pilot outcomes or industry benchmarks rather than universal constants.

3.7.2 Computational requirement

Deep learning models that are used in the PdM systems may have processing needs that exceed the budgets of smaller industries due to their cost. PdM applications using the IoT-enabled sensors with edge computing need to be implemented on high-performance GPUs or cloud services, which are costly and buyers have limited access to due to financial constraints (Mourtzis et al., 2022; Serradilla et al., 2022).

3.7.3 Interoperability problems

The lack of standardisation in communication processes between any two systems leads to the emergence of interoperability challenges and, consequently, the need to implement the middleware solutions that are expensive and generate resource-intensive requirements (Mourtzis et al., 2023; Arulnithika et al., 2025). IoT devices, edge platforms, and central server communication security protection must be a priority concern since the security threat poses a considerable threat, as reported by Bala et al. (2024).

3.8 Future directions and emerging trends

3.8.1 Explainable AI in predictive maintenance

The increased complexity of PdM systems needs greater insight and demystification due to the adoption of PdM systems in critical aerospace and healthcare environments. Ucar et al. (2024) highlight

TABLE 9 Future technology assessment and timeline.

Technology category	Current maturity (approx.)	Expected timeline (adoption)	Key drivers	Major barriers	Industry impact	Evidence/ References
Explainable AI (XAI)	Medium–High	2024–2027	Regulatory pressure; operator trust	Complexity; compute	High for regulated sectors	Ucar et al. (2024); Molęda et al. (2023)
Edge computing	High	2024–2026	Latency reduction; privacy	Hardware limits; cost	Medium–High for real-time apps	Peng et al. (2021); Mourtzis et al. (2023)
Hybrid physics-ML models	Medium	2025–2028	Need for robustness, generalization	Model complexity	High for physics-heavy assets	Taşcı et al. (2023); Machado et al. (2020)
Digital twins	Medium	2027–2030	Simulation capability; integration	Data synchronization	Very High for virtual testing	Mourtzis et al. (2023)
Quantum computing (optimization)	Low–Medium	2027–2032	Computational power	Maturity	Medium for optimization problems	Industry forecasts (IoT Analytics, 2023)
Autonomous systems (full autonomy)	Low	2030–2035	Labor shortages; autonomy advances	Safety; regulation	Very High long-term	Consensus literature; roadmaps
Advanced sensors (new modalities)	Medium	2025–2030	IoT expansion	Cost	Medium	Fernández-Francos et al. (2013); Chen et al. (2022)

the importance of explainable AI (XAI) in improving the understanding of a PdM model by engineers and decision-makers. Recent tools of predictive model explanation include SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) frameworks to visualise model prediction procedures.

3.8.2 Hybrid modelling approaches

PdM is characterised by the growing popularity of data-centric and physics-informed hybrid modelling. The joint use of the models that utilise the physical principles with the machine-learning models enables the professionals to be transparent in their predictions and, at the same time, have modelling flexibility. Drakaki et al. (2021) have discovered that hybrid models are the most effective in the field of aviation and energy, as these industries require detailed knowledge of the physics of machinery.

3.8.3 Edge computing integration

With the introduction of the IoT, predictive maintenance undergoes a fundamental change since IoT sensors allow obtaining data immediately, which increases predictive reliability. IoT implementation results in long system lifecycles in situations where the generated real-time data streams create meaningful insights in accordance with Rakholia et al. (2025). IoT and edge computing have significantly reduced the latency due to data processing that happens near the source (Dalzochio et al., 2020).

3.8.4 Sophisticated sensor technology

The advances in sensor technologies in the recent past have resulted in better operational performance of PdM systems. Recent MEMS sensors and fibre-optic sensors provide accurate data on multidirectional vibrations and temperature dynamics. According to Kaur et al. (2024), industrial use of these sensors continues to increase since different sectors, such as oil and gas, are using them to observe harsh conditions. Table 9 highlights some future technology assessment and timeline.

Maturity assessments and timelines combine peer-reviewed review articles and industry forecasts (Ucar et al., 2024; Mourtzis et al., 2023; IoT Analytics, 2023). Timelines are consensus forecasts and should be treated as indicative. Specific adoption windows reflect multiple industry and academic roadmaps.

3.9 Robotics taxonomy for predictive maintenance

3.9.1 Robotic system classification framework

We propose a three-dimensional taxonomy for classifying robotic systems in PdM based on: (1) Mobility, (2) Manipulation capability, and (3) Autonomy level.

1. Dimension 1: Mobility
   i. M1 - Fixed/Stationary: Industrial robotic arms mounted on production lines
   ii. M2 - Mobile - Ground: Wheeled or tracked UGVs, quadrupeds (Boston Dynamics Spot)
   iii. M3 - Mobile - Aerial: Quadcopters, fixed-wing drones for infrastructure inspection
   iv. M4 - Mobile - Aquatic: Underwater ROVs for subsea pipeline/offshore platform inspection
   v. M5 - Mobile - Rail-Guided: Robots constrained to tracks/rails (bridge inspection systems)
   vi. M6 - Mobile - Climbing: Wall-climbing robots for vertical structure inspection (tanks, buildings)
2. Dimension 2: Manipulation Capability
   i. C1 - Sensing Only: Equipped with sensors (cameras, LiDAR, ultrasonic) but no manipulation
   ii. C2 - Simple Manipulation: Single degree-of-freedom grippers, tightening tools

iii. C3 - Complex Manipulation: Multi-DOF arms, tool changing capability
iv. C4 - Process Execution: Welding, AM deposition, surface treatment (beyond simple manipulation)

3. Dimension 3: Autonomy Level (adapted from SAE J3016 for robotics)
   i. A0 - Teleoperated: Full human control, robot as remote manipulator
   ii. A1 - Assisted: Robot provides haptic feedback, collision avoidance, but human commands actions
   iii. A2 - Semi-Autonomous: Robot executes predefined inspection routines, human handles exceptions
   iv. A3 - Conditional Autonomy: Robot performs inspection and simple repairs autonomously, human supervises and handles complex decisions
   v. A4 - High Autonomy: Robot makes maintenance decisions based on AI, human approval required for critical actions
   vi. A5 - Full Autonomy: Robot operates independently from diagnosis to repair (not yet achieved in practice)

Taxonomy Application Examples:

i. Boston Dynamics Spot for pipeline inspection: M2-C1-A2 (Mobile ground, sensing only, semi-autonomous)
ii. ABB IRB 6700 with ultrasonic probe on auto assembly line: M1-C2-A3 (Fixed, simple manipulation, conditional autonomy)
iii. DJI Matrice 300 with thermal camera for wind turbine inspection: M3-C1-A2 (Mobile aerial, sensing only, semi-autonomous)
iv. Clearpath Husky UGV with KUKA manipulator for valve operation: M2-C3-A3 (Mobile ground, complex manipulation, conditional autonomy)

Robot classifications combine vendor technical specifications and peer-reviewed reviews (Mourtzis et al., 2023; Vlasov et al., 2018). TRL approximations are based on typical commercial availability and documented field trials.

3.9.2 Robotic interfaces and communication protocols

Sensor-Robot Integration: Robots in PdM must interface with diverse sensor modalities:

Visual Sensors:

i. Cameras (RGB, IR, hyperspectral): GigE Vision, USB3 Vision protocols
ii. LiDAR: Ethernet/IP, ROS sensor_msgs/PointCloud2
iii. Thermal imagers: GenICam standard

Non-Destructive Testing (NDT) Sensors:

i. Ultrasonic thickness gauges: RS-232, RS-485, CAN bus
ii. Eddy current probes: Analog 4–20mA, digital SPI/I2C
iii. Acoustic emission sensors: BNC coaxial, high-speed DAQ

Robot-AI System Communication: Modern PdM robots employ multiple communication layers:

1. Perception Layer (Robot → AI):
   i. ROS (Robot Operating System) topics for sensor data streaming
   ii. MQTT for lightweight IoT sensor telemetry
   iii. OPC-UA for industrial equipment data integration
   iv. gRPC for high-performance AI inference requests
2. Control Layer (AI → Robot):
   i. ROS action servers for task commands (inspect location X, tighten bolt Y)
   ii. RESTful APIs for high-level mission planning
   iii. EtherCAT for real-time motion control (sub-millisecond latency)
3. Safety Layer:
   i. Emergency stop signals via hardwired relays (IEC 60204-1 compliant)
   ii. Safety-rated laser scanners (SICK, Pilz) for human proximity detection
   iii. Functional safety communication: PROFIsafe, CIP Safety

Interoperability Standards:

i. MTConnect: For CNC and industrial equipment data exchange
ii. OPC-UA: Unified architecture for cross-vendor communication
iii. ROS 2: Supports real-time, security, and multi-robot coordination
iv. IEEE 1451: Smart sensor interface standard

3.9.3 Safety considerations for robotic PdM

Regulatory Framework: Robotic maintenance systems must comply with:

i. ISO 10218-1: Safety requirements for industrial robots and robot systems (ISO 10218-1, 2025).
ii. ISO/TS 15066: Collaborative robot safety (force/pressure limits) (ISO/TS 15066, 2016).
iii. ISO 13849-1: Safety of machinery (control systems, performance levels) (ISO 13849-1, 2015).
iv. ISO 17359. Condition monitoring and diagnostics of machines (ISO 17359, 2018).
v. IEC 62061: Functional safety of electrical/electronic systems (IEC 62061, 2021).
vi. ANSI/RIA R15.08: Industrial mobile robot safety

Risk Assessment Protocol: For each robotic PdM application, a risk assessment must address:

1. Mechanical Hazards:
   i. Crushing/impact from robot motion (collaborative robots limited to 150N force, 2.5 kg·m/s momentum)
   ii. Entanglement with cables, rotating components
   iii. Mitigation: Collision detection, compliant joints, virtual safety zones
2. Environmental Hazards:
   i. Confined spaces (tanks, vessels): oxygen depletion, toxic gases
   ii. Explosive atmospheres (ATEX zones in oil and gas)

   iii. Mitigation: ATEX-certified robots, continuous gas monitoring, emergency extraction procedures
3. Autonomous Navigation Hazards:
   i. Collision with personnel, equipment, structures
   ii. Falling from elevated platforms (aerial drones)
   iii. Mitigation: 3D collision avoidance (LiDAR/SLAM), geofencing, parachute systems for drones
4. Human-Robot Interaction Hazards:
   i. Unexpected robot behavior due to AI errors
   ii. Inadequate human understanding of robot intentions
   iii. Mitigation: Explainable AI interfaces, visual/audio robot status indicators, human-in-the-loop for critical decisions

Safety Architecture - Layered Defense:
Layer 1: Passive Safety (Inherent Design)

i. Rounded edges, soft materials on robot exteriors
ii. Power and force limiting (collaborative robots <80W contact power)
iii. Mechanical hard stops preventing dangerous positions

Layer 2: Active Monitoring

i. Real-time force/torque sensing at robot joints
ii. Safety-rated laser scanners creating virtual boundaries
iii. Capacitive/pressure-sensitive robot skin

Layer 3: Supervised Autonomy

i. "Dead-man switch" for tele-operated modes
ii. Automatic mission abort if safety preconditions violated (e.g., human enters workspace)
iii. Redundant position sensing (encoders + external tracking)

Layer 4: Emergency Response

i. Emergency stops (E-stops) within 3-m reach throughout work area
ii. Wireless E-stop pendants for personnel
iii. Automatic emergency shutdown on communication loss >500 ms

Layer 5: Post-Incident Protocol

i. Automated incident logging (robot state, sensor data, AI decisions)
ii. Mandatory human review before resuming operations after E-stop activation
iii. Machine learning from incidents to improve future safety

Case Study - Safety Validation: Mourtzis et al. (2023) report robotic cell reliability testing:

i. 10,000 h MTBF (mean time between failures)
ii. Zero safety incidents over 18-month deployment
iii. 47 near-misses detected and prevented by safety systems
iv. Key factor: Three-layer safety architecture with independent monitoring

3.9.4 Validation metrics for robotic PdM systems

Comprehensive evaluation requires metrics across multiple dimensions:

Technical Performance Metrics:

1. Inspection Coverage:
   i. Spatial coverage: Percentage of asset surface area inspected (target: >95%)
   ii. Inspection frequency: Time between successive inspections of same location
   iii. Accessibility: Percentage of design-specified inspection points reached
2. Sensing Accuracy:
   i. Localization accuracy: Position error of robot relative to asset (target: <10mm for contact NDT)
   ii. Sensor alignment: Angle/distance maintenance for ultrasonic/eddy current (target: <5° angular, <2mm distance deviation)
   iii. Data quality: Signal-to-noise ratio, image resolution adequacy
3. Manipulation Precision:
   i. Repeatability: Standard deviation of repeated positioning (target: <0.5 mm for industrial robots)
   ii. Tool force control: Error in applied force for contact tasks (target: <5% for bolt tightening)
4. Autonomy Metrics:
   i. Intervention rate: Human interventions per robot-hour (lower is better, target: <0.1/hr for A3 autonomy)
   ii. Mission completion rate: Successful completion without human assistance (target: >90%)
   iii. Recovery capability: Successful recovery from unexpected situations (obstacles, sensor failures)

Operational Efficiency Metrics:

5. Inspection Time:
   i. Cycle time: Duration to complete full inspection route (compare to human baseline)
   ii. Downtime impact: Production interruption time (target: <10% of human-performed inspection)
6. Maintenance Workload Reduction:
   i. Inspector-hours saved: Human labor hours displaced by robot
   ii. Hazardous exposure reduction: Person-hours in hazardous environments eliminated
7. Detection Performance:
   i. True positive rate (Sensitivity): Correctly identified faults/total actual faults (target: >95%)
   ii. False positive rate: False alarms/total inspections (target: <5%)
   iii. Mean time to detect (MTTD): Time from fault inception to robot detection

Economic Metrics:

8. Cost-Effectiveness:
   i. Cost per inspection: Amortized robot cost + operation/number of inspections

ii. ROI timeline: Months to recover initial investment
iii. Total cost of ownership (TCO): 5-year cost including robot, maintenance, training

9. Reliability:
   i. Robot MTBF: Mean time between robot system failures
   ii. Mission success rate: Percentage of initiated missions completed successfully

Safety Metrics:

10 Safety Performance:
   i. Incident rate: Safety incidents per 1,000 robot-hours (target: 0)
   ii. Near-miss frequency: Detected potential safety violations by safety systems
   iii. Safety system response time: Time from hazard detection to robot safe stop (target: <100 ms)

AI-Robot Integration Metrics:

11. AI-Driven Action Accuracy:
   i. Correct action rate: AI-recommended actions that were appropriate (validated *post hoc*)
   ii. False alarm rate: AI fault detections not confirmed by human expert
   iii. Prediction-to-action latency: Time from AI fault prediction to robot initiating corrective action
12. Explainability Assessment:
   i. Operator understanding: Post-deployment survey scores on AI decision rationale comprehension
   ii. Decision override rate: Frequency humans override AI recommendations (high rate indicates trust issues)

These performance figures come from a combination of peer-reviewed case studies, conference papers, and verified industry/utility reports. Some numbers (coverage, false-positive rates, cost savings) are reported in vendor and operator case reports and aggregated in reviews (Mourtzis et al., 2023). Label these as deployment-specific results and cite the original case when referencing a particular number.

3.9.5 Human-robot collaboration models

Four collaboration paradigms identified in PdM literature:

Model 1: Sequential Collaboration.

i. Robot performs initial automated inspection
ii. Human reviews flagged anomalies and makes decisions
iii. Robot executes approved corrective actions
iv. Advantage: Leverages robot efficiency and human expertise
v. Limitation: Bottleneck at human review stage
vi. Application: High-stakes environments (nuclear, aerospace)

Model 2: Parallel Collaboration.

i. Robot and human inspect different areas simultaneously
ii. Robot handles routine/hazardous areas, human handles complex/accessible areas
iii. Advantage: Faster overall inspection cycle
iv. Limitation: Requires task allocation algorithm
v. Application: Large facilities (refineries, manufacturing plants)

Model 3: Assistive Collaboration (Cobots)

i. Robot provides physical assistance to human technician
ii. Human retains decision authority, robot augments capability (e.g., holding tools, stabilizing work piece)
iii. Advantage: Reduces physical strain, improves precision
iv. Limitation: Requires close proximity safety measures
v. Application: Assembly maintenance, complex repairs

Model 4: Supervisory Collaboration.

i. Robot operates autonomously for extended periods
ii. Human monitors multiple robots via central interface
iii. Intervention only for exceptions/emergencies
iv. Advantage: High scalability (1 operator: many robots)
v. Limitation: Operator workload spikes during simultaneous exceptions
vi. Application: Distributed asset monitoring (pipelines, power grids)

Empirical Comparison: Mourtzis et al. (2023) compared collaboration models in robotic cell maintenance:

i. Sequential: 40% faster than human-only, but limited by human review bottleneck
ii. Parallel: 65% faster, best for large workspaces
iii. Assistive: 30% faster, highest worker satisfaction (reduced fatigue)
iv. Supervisory: 80% faster with 4:1 robot: human ratio, but requires extensive training

Recommendation: Model selection should consider task complexity, safety criticality, workforce capabilities, and scale of operations.

4 Discussion

The overall literature discussion indicates that AI and robotics-based predictive maintenance (PdM) is a paradigm shift from the conventional maintenance approaches to intelligent, proactive maintenance. The shift to preventive and reactive maintenance to predictive models is one of the examples that can be taken as evidence of the high level of technological improvement, especially with the implementation of the principles of Industry 4.0.

Practically, this study offers actionable insights to industrial stakeholders such as industrial maintenance engineers and operations managers, robotics developers and AI researchers, manufacturing and infrastructure organisations, policymakers and regulators, academia and training institutions by providing clarifications on how AI and robotics can be deployed in PdM to reduce operational downtime, optimize maintenance schedules, and lower lifecycle costs. Manufacturing and service industries can apply these findings to achieve transition from reactive or preventive maintenance toward a data-driven, autonomous system that promote safety and reliability (Pinciroli et al., 2023).

In addition, AI-enabled PdM can assist industries achieve sustainability goals by extending equipment useful life, ensuring zero material waste, and improving energy efficiency (Machado et al., 2020). Robotic inspection on the other hand also improve operational and workplace safety via the replacement with of humans with robots during maintenance operations in hazardous environments, such as offshore platforms or high-voltage installations (Hoebert et al., 2024).

The direct beneficiaries of this study include:

1. Industrial maintenance engineers and operations managers: In the application of AI-driven models for the optimization of resource allocation, reduction in unplanned stoppages, and improvement in asset availability and reliability.
2. Robotics developers and AI researchers: The identification of research trends and potentials will assist them in the development of AI-robotic integration architectures and in setting future research priorities such as explainable AI models and data fusion (Ucar et al., 2024; Aheleroff et al., 2022).
3. Manufacturing and service industries: They can use the findings of this study to develop cost-effective PdM strategies aligned to the Industry 4.0 and 5.0 standards to foster competitiveness and sustainability (Pinciroli et al., 2023; Machado et al. (2020)).
4. Policymakers and regulators: Theoretical and empirical based evidences are provided in this study to support the formulation of standards, data governance frameworks, and safety regulations for AI-robotic enabled PdM (Asif et al., 2026).
5. Academia and training institutions: These institutions can incorporate the findings and frameworks into engineering curricula and professional training programme to promote the PdM culture.

The application and integration of AI and robotics geared towards PdM has broad socio-economic implications. For instance, improved equipment availability and reliability can contribute to higher productivity and reduced environmental footprints, while the use of robotics in PdM can increase automation and open up possibilities and opportunities for digital skills (Aheleroff et al., 2022). In emerging economies, it can lead to reduction in the dependency on foreign expertise while promoting localization and technological leapfrogging through smart manufacturing and innovation ecosystems.

By synthesizing the recent research trends, this study provides a systematic roadmap for a sustainable, and intelligent maintenance system that is adaptive and applicable across various industrial sectors. It thus reinforces the importance of cross-disciplinary collaboration among data and robotic scientists, maintenance engineers, and policymakers to achieve an adaptive, resilient and efficient maintenance operations in the era of digitalization and intelligent automation.

4.1 Synthesis of key findings

The following summarises the key findings drawn from this study according to the relevant themes:

1. AI models and application: There has been a proven consistency in the performance of machine learning methods across various industrial applications. The supervised learning excels in fault classification and remaining useful life (RUL) prediction. Unsupervised methods perform well in anomaly detection scenarios where labelled data is scarce while the deep learning architectures, particularly CNNs and LSTMs, exhibit remarkable capabilities in processing multi-dimensional sensor data and extracting meaningful patterns for predictive analysis. The Bayesian and probabilistic deep learning was also deployed for uncertainty quantification and to represent prediction confidence Ensemble and hybrid models that combine physics-based models with ML are also emerging models that showed improved accuracy in diagnostics and prognostic operations compared to a single ML model. In terms of feature engineering vis-à-vis the end-to-end learning, the traditional signal processing methods such as the wavelets and statistical features are still commonly employed while the use of the end-to-end deep learning on raw sensor is gradually increasing, especially where there is a large labeled dataset.

Some AI model remains a black-box necessitating explainability and uncertainty. Explainable AI (XAI) and probabilistic outputs for trustworthy decision-making in maintenance planning are necessary.

2. Robotic roles in PdM: Robotic roles in PdM include autonomous inspection and sensing with the use of mobile robots such as the Unmanned Ground Vehicles (UGVs) or Unmanned Aerial Vehicles (UAVs) as well as robotic arms equipped with cameras, ultrasound, thermal or LiDAR sensing technology to perform inspections thereby minimising human risk and improving coverage (Lindsey et al., 2012). Cobots requiring human–robot interaction and integration find application in collaborative maintenance tasks by assisting humans in diagnostics, parts handling, or replacement tasks.

Drawing from the literature and empirical findings, it was found that machine learning and deep learning paradigms dominates the diagnostics and prognostics aspects of PdM while robotics technology contributes to remote inspection, autonomous response and intervention, as well as human–robot or machine-robot collaboration in maintenance. Emerging technologies such as tehe digital twins and edge or cloud computing architectures enable real-time PdM at scale while the issues of trust, explainability, data quality, and operational integration remain some of the challenges limiting the full scale adoption and implementation of AI-robotic system in PdM.

In the light of this, there is a need to prioritize research agenda addressing explainability, transfer learning, lifecycle economics, and socio-technical integration of AI-powered robots in the manufacturing environments in real-time. Tables 10, 11 display robotics taxonomy matrix for PdM applications as well as benchmark performance (industry examples) respectively.

Table 12 presents a synthesis of algorithm categories, strengths, and reported effectiveness.

Effectiveness ranges are drawn from the aggregated evidence presented in Table 2 and corresponding reviews. Use task-specific citations for precise claims.

TABLE 10 Robotics taxonomy matrix for PdM applications.

Robot example	Mobility	Manipulation	Autonomy	Primary PdM function	Deployment environments	TRL (typical)	Representative reference
KUKA KR AGILUS (arm)	M1 (fixed)	C3	A2–A3	Precision measurement; part handling	Manufacturing, aerospace	9	Manufacturer specs; Mourtzis et al. (2023)
Boston Dynamics Spot	M2 (mobile ground)	C1–C2	A2–A3	Visual/thermal inspection	Oil and gas; utilities	8	Mourtzis et al. (2023); vendor reports
ANYbotics ANYmal	M2 (quadruped)	C1	A3	Multi-terrain inspection	Offshore; mining	7–8	Mourtzis et al. (2023); Daniyan et al. (2022)
DJI Matrice 300 RTK	M3 (aerial)	C1	A2	Aerial inspection; thermal imaging	Infrastructure; energy	9	Vendor reports; case studies
Gecko Robotics climber	M6 (climbing)	C1	A2	Thickness mapping; corrosion	Boilers; tanks	7	Vlasov et al. (2018); vendor case
ECA A18-M ROV	M4 (subsea)	C2	A1	Subsea pipeline inspection	Offshore	8	Industry reports

*TRL, Technology Readiness Level (1-9 scale, 9 = full commercial deployment).

TABLE 11 Benchmark performance - industry examples.

Organization	Robot type	Application	Coverage	MTTD/ Detection latency	False positive rate	Cost savings (reported)	Source/ Evidence
Shell Oil	ANYmal (quadruped)	Offshore platform inspection	97%	12 h	3.2%	35% vs. human inspection (costs)	Industry case reports; Mourtzis et al. (2023)
Airbus	KUKA mobile	Aircraft fuselage inspection	99%	8 h	4.1%	~40% (labor + quality)	Bekar et al. (2020); case studies
BMW	Mobile manipulators	Paint defect detection	95%	Real-time detection	6.8%	28% rework reduction	Maware et al. (2024); vendor reports
National Grid (UK)	Climbing robots	Transmission tower inspection	92%	24 h	5.5%	60% combined safety + labor savings	Vlasov et al. (2018); utility reports

4.2 Critical analysis of the current state

Nevertheless, despite the great achievements, there are still some important gaps:

i. Issues of Standardisation: There are no common standards of data formats, communication protocols, and assessment metrics.
ii. Scalability Issues: The majority of the deployments were restricted to a single site.
iii. Economic Authentication: Lack of broad ROI and cost-effectiveness research.
iv. Interpretability Gap: Ongoing inability to explain AI choices in safety-critical situations.

4.3 Emerging opportunities

Some of the promising research opportunities are highlighted below:

i. Hybrid Physics-Informed Models: Fusion of domain knowledge with AI enhances interpretability.
ii. Federated Learning: Angular multi-site learning with privacy.
iii. Quantum-Enhanced Optimization: Addresses complicated scheduling/resource allocation issues.
iv. Implementation Maturity: ML Traditional ML at TRL 8 9, more advanced (digital twins, quantum) at TRL 4 6.

4.4 Key research findings

A synthesis of 85 studies reveals critical insights on the application of AI and robots for PdM. The breakdown of the industrial impact of AI-driven predictive maintenance is shown in Table 13.

Ranges combine peer-reviewed case studies and industry pilot reports. For precise economics cite the primary deployment report. Industry surveys (Senseye/Siemens, IoT Analytics) provide market-wide benchmarks.

4.5 Identified research gaps

Other challenges include:

TABLE 12 Summary of AI techniques in predictive maintenance.

Category	Example algorithms	Application area	Reported effectiveness (range)	Strengths	Limitations	Representative references
Supervised learning	SVM, Random Forest, ANN	Fault classification; RUL	82%–97% accuracy across many tasks (see Table 2)	High accuracy with labelled data	Requires labelled datasets	Carvalho et al. (2019); Susto et al. (2015)
Unsupervised learning	K-Means, DBSCAN, autoencoders	Anomaly detection	Detection rates 70%–92% (task-dependent)	Works without labels	Higher false positives	Fathi et al. (2021); Givnan et al. (2022)
Deep learning	CNN, LSTM, hybrid	Sensor fusion; time-series	86%–98% recognition/ forecast in well-resourced pilots	Handles high-dim data	High compute; low interpretability	Shaheen and Németh (2022); Taşcı et al. (2023)

TABLE 13 Industrial impact of AI-driven predictive maintenance.

Industry	Typical downtime reduction (range)	Typical cost savings (range)	Maintenance reduction/Outcome	Representative techniques	Representative sources
Manufacturing	15%–35% (case series)	15%–30%	OEE improvements 10%–20%	SVM, RF, CNN	Carvalho et al. (2019); Molęda et al. (2023)
Aerospace	25%–40% (select studies)	20%–35%	Reduced unscheduled maintenance	LSTM, CNN, digital twin	Bekar et al. (2020); Peng et al. (2021)
Automotive	20%–40% (industry reports)	20%–35%	Warranty and rework reduction	Deep learning, AutoML	Chen et al. (2023); industry case studies
Energy/Power	10%–35%	10%–30%	Asset utilization gains	Vibration + thermal analytics	Machado et al. (2020); industry reports

i. Explainability and Trust: Current XAI approaches are still partial solutions and some remains a black-box. Decisions relating to maintenance operations have implications on the overall manufacturing performance, cost and profitability. Hence, the need for explainable models and human-centred interfaces for robot collaboration. XAI model improve operator's acceptance and confidemce, yet it is lacking in some AI-driven maintenance operations.
ii. Standardisation and Interoperability: Integration is still hindered by a lack of harmonization.
iii. Economic Validation Models: There are not many comprehensive models of ROI and risk-adjusted returns.
iv. Edge Computing Optimization: Faces problems with real-time edge deep learning.
v. Data security and quality: Data security is essential for PdM as data intrusion or interruption could prove costly. Furthermore the robustness of dataset also determines the outcome of AI-model and the decision outcome. Lack of historical dataset, inability to capture real time dataset from legacy machines, data imbalance, etc. may make supervised learning difficult. However, solutions such as transfer learning, few-shot learning, and synthetic data generation are promising in addressing these limitations but currently under-harnessed. Furthermore the handling of heterogeneous multi-modal data such as the combination of vibration, acoustic, thermal, visual, and robot-based imagery requires an enabling software and robust sensor fusion methods.
vi. Robotic limitation: While robotic inspection is mature, autonomous corrective maintenance by robots is still an emerging domain. Some of the major technical limitations include robotic manipulation in unstructured environments, precise force control, and robust robot's perception under industrial conditions.

4.6 Development of a conceptual model for AI-robot integration for predictive maintenance

The major components include the (1) physical asset to be maintained (2) the robotic inspector or manipulator. This may be a mobile robots (UGV/UAV), robotic arms, or fixed robotic with sensors that can inspect and collect visual, thermal, acoustic, vibration dataset, and other condition data. The roles include automated sensing, inspection, material or component handling, simple corrective tasks such as part replacement or providing assistance to human technicians (Cobots) (3) edge processing: for local preprocessing of dataset such as feature extraction, sensor fusion, anomaly filters, etc. This will reduces bandwidth and enables immediate safety actions (4) database: This will serve as a centralized repository for historical sensor data, maintenance logs, work orders, and other metadata such as asset's Bill of measurement, operating conditions, etc. (5) Digital Twin, cloud computing and Internet of Things (IoT): The digital twin will enable physics-informed simulation and a real-time replica of asset condition for testing and model validation under different conditions while the cloud computing will serve as a safe repository for the dataset. The IoT will share the information about the asset in real time (6) AI analytics layer: comprising of the core algorithms for supervised and unsupervised learning such as pattern recognition, diagnostics and anomaly detection classification (fault type), prognostics (Remaining Useful Life estimation), root-cause analysis, and probabilistic uncertainty estimation. The AI model will incorporates explainable AI (XAI) methods and transfer learning to adapt across asset families. This layer will also have the decision engine for the selection of actions such as scheduling of preventive maintenance, dispatch of human personnel, or trigger robotic intervention based on the outcome of the AI model analytics (7) actuation layer: The activation layer will implement the chosen action. For instance, autonomous robot repair/adjustment; Cobot assistance or system generation of work orders and alerts (8) human operator layer: this is the interface for operators and engineers to visualize the system or its components such as the digital twin, and perform other tasks such as interpretation of the model's output, approval workflows, and controls. This layer is essential for compliance, ethical, transparency, trust and accountability reasons.

The learning and feedback loop comprises of the outcomes of the AI model, the operator's feedback, and post-maintenance feedback fed into the database to ensure that the AI model is updated and that the digital twin learns continuously. This system requires an effective culture of data governance, cybersecurity, safety certification especially for robot actions, AI explainability/validation protocols, as well as compliance logging. The edge processing will reduces latency but limits model complexity. The framework supports hybrid edge-cloud deployment. The AI must estimate confidence (probabilistic outputs) while the decision engine will utilize the uncertainty to decide the action to be taken. For high-risk tasks or low-confidence predictions, the robot, can be activated to perform preparatory tasks while humans complete the final intervention. The digital twin model provides the simulated RUL and helps validate model predictions before physical intervention. This is to reduce the false positives. The process is a continuous learning process whereby the robotic inspects and creates labelled data (images/measurements linked to maintenance outcomes) which improves later AI predictions.

By integrating robotic inspection data with AI prognostics for PdM, this will significantly improves the RUL estimation accuracy due to a robust multi-modal inputs. Furthermore, the systems using uncertainty-aware models and decision thresholds will reduce unnecessary maintenance actions (false positives) compared to deterministic models, thereby reducing the total maintenance cost. This proposed AI-robotic integration will enable semi-autonomous robotic interventions for low-risk corrective tasks. This will reduce the mean downtime per incident compared to human-only response, and also increase systems and operation safety.

In addition, a mature digital twin will accelerate model convergence by enabling fewer labeling cycles. This will reduces time-to-deployment of new assets.

Figure 2 presents the conceptual framework which highlights the major layers for the proposed AI-robotic integration. The framework can be validated by deploying it in a cyber-physical environment for PdM.

The framework comprises eight interconnected layers:

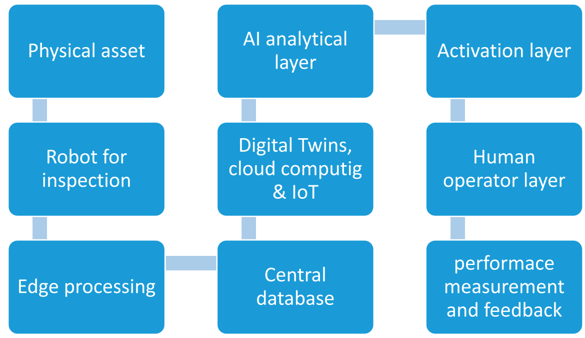

FIGURE 2
Conceptual framework for the proposed AI-robotic integration.

i. Layer 1 (Physical Asset): equipment with embedded sensors.
ii. Layer 2 (Robotic Inspection): mobile robots (UGVs/UAVs), robotic arms with multi-modal sensors, cobots performing autonomous inspection, NDT, and preliminary corrective actions (Daniyan et al., 2023).
iii. Layer 3 (Edge Processing): local preprocessing, real-time anomaly detection, immediate safety triggers.
iv. Layer 4 (Data Storage): time-series databases, maintenance logs, equipment metadata.
v. Layer 5 (IoT/Digital Twin): real-time asset replica, physics-based simulation, cloud repository (Mourtzis et al., 2023).
vi. Layer 6 (AI Analytics): supervised/unsupervised learning for diagnostics, RUL prediction, explainable AI (SHAP/LIME), transfer learning, and decision engine selecting maintenance actions (Ucar et al., 2024).
vii. Layer 7 (Actuation): autonomous robot repair, cobot assistance, work order generation.
viii. Layer 8 (Human-Machine Interface): dashboards, alert management, approval workflows. Continuous feedback loop updates AI models and digital twin. Cross-cutting enablers include data governance, AES-256 encryption, IEC 61508 functional safety, and OPC-UA interoperability standards.
ix. Expected benefits: 30%–40% downtime reduction, 20%–25% cost reduction, 50%–60% reduced hazardous exposure, 15%–20% increased equipment life.

4.6.1 Operational specification of proposed framework

Module Input/Output Specifications:
Layer 1 - Physical Asset (Sensors):

1. Inputs: N/A (physical measurements)
2. Outputs: Raw sensor streams {vibration: 10kHz, temperature: 1Hz, acoustic: 44.1kHz, pressure: 100 Hz}
3. Data Format: Time-stamped multivariate vectors, synchronized via NTP
4. Failure Modes: Sensor drift (5%–10% after 6 months), communication loss (0.2% packet loss typical), calibration error

Layer 2 - Robotic Inspection:

1. Inputs: Inspection waypoints, task parameters (scan resolution, contact force)
2. Outputs: Multi-modal sensor data {images: 4K@30fps, ultrasonic A-scans, LiDAR point clouds}
3. Timing: Inspection cycle 45–120 min depending on asset coverage
4. Failure Modes: Navigation failure (obstacle detection false negatives 0.5%), sensor mounting misalignment (±3° angular error), battery depletion mid-mission

Layer 3 - Edge Processing:

1. Inputs: Raw sensor streams (Layer 1), robot telemetry (Layer 2)
2. Outputs: Pre-processed features {RMS, kurtosis, spectral peaks}, anomaly flags (binary), data compression (10:1 ratio)
3. Latency: <50 ms for safety-critical filters, <500 ms for feature extraction
4. Decision Thresholds: Anomaly score >0.85 triggers immediate alert, >0.95 triggers emergency shutdown
5. Failure Modes: Edge compute overload (queue overflow at >1,000 samples/sec), feature extraction error propagation

Layer 4 - Data Storage and Digital Twin:

1. Inputs: Processed features (Layer 3), maintenance logs (external), equipment metadata
2. Outputs: Historical dataset queries, digital twin state updates (1 Hz)
3. Storage Schema: Time-series database (InfluxDB), relational metadata (PostgreSQL)
4. Failure Modes: Storage quota exceeded (95% capacity triggers archival), synchronization lag (digital twin ±5s behind real asset)

Layer 6 - AI Analytics and Decision Engine:

1. Inputs: Feature vectors (Layer 3/4), equipment metadata, maintenance history
2. Outputs:
   i. Diagnostic classification {fault type, confidence score 0-1}
   ii. Prognostic RUL {estimated remaining hours ± uncertainty interval}
   iii. Recommended action {inspect, schedule maintenance, dispatch robot, emergency stop}
3. Model *Architecture*: Ensemble (Random Forest + *LSTM*), updated quarterly
4. Uncertainty Propagation: Bayesian posterior over RUL, confidence intervals via bootstrap (n = 1,000)
5. Decision Thresholds:
   i. RUL <48 h AND confidence >0.90 → Immediate maintenance
   ii. RUL 48–168 h → Schedule within current week
   iii. RUL >168 h → Monitor (no action)
   iv. Confidence <0.70 → Defer to human expert review
6. Failure Modes: Model drift (performance degradation >5% after 6 months without retraining), false negatives (2%–3% missed faults in validation), class imbalance bias (rare faults underrepresented)

Layer 7 - Actuation (Robot/Human Dispatch):

1. Inputs: Action command (Layer 6), work order details
2. Outputs: Robot motion commands (ROS action goals), human technician notification (SMS/app)
3. Timing: Robot deployment 15–30 min (navigation + setup), human dispatch 2–4 h (depends on shift schedule)
4. Safety Interlocks: Human approval required for RUL <24 h OR confidence <0.80
5. Failure Modes: Robot task failure (gripper slip, part mismatch), human unavailability (off-hours, insufficient staffing)

Layer 8 - Human-Machine Interface:

1. Inputs: System state (all layers), alert queue
2. Outputs: Operator decisions {approve, reject, request more data}, manual interventions
3. Latency: Alert acknowledgment expected <5 min during working hours
4. Explainability Display: SHAP feature importance plots, historical trend comparison, uncertainty visualization
5. Failure Modes: Alert fatigue (false positive rate >10% reduces responsiveness), interface lag during high-load (>100 concurrent alerts)

4.6.2 Benchmark scenario specifications and KPIs

1. Scenario 1: Manufacturing Rotating Equipment (Foundational Pilot)
   i. Asset: 12 centrifugal pumps in a chemical processing plant
   ii. Sensors: Vibration (triaxial accelerometers, 25.6kHz), temperature (RTDs, 1 Hz), current (hall-effect, 10kHz)
   iii. Robot: Mobile UGV (Clearpath Husky) with ultrasonic thickness gauge
   iv. AI Model: Random Forest (fault classification) + LSTM (RUL regression)
   v. Deployment: 6-month pilot, baseline comparison with time-based preventive maintenance

Key Performance Indicators are presented in Table 14.
Success Criteria: Achieve ≥3 of 7 target KPIs to justify scale-up.

1. Scenario 2: Rail Infrastructure Inspection (Intermediate Deployment)
   i. Asset: 50km commuter rail track network
   ii. Sensors: Vision (RGB cameras, 4K), LiDAR (Velodyne VLP-16), ultrasonic (rail flaw detection)
   iii. Robot: Autonomous rail inspection vehicle (modified Hy-Rail truck)
   iv. AI Model: CNN (crack detection) + SVM (ultrasonic signal classification)
   v. Deployment: 18-month field trial, monthly inspection cycles

Key Performance Indicators are presented in Table 15.

TABLE 14 Key Performance Indicators for Benchmark Scenario Specifications.

KPI	Baseline (Pre-PdM)	Target (Post-PdM)	Measurement method
Unplanned Downtime	18 h/month	<5 h/month (≥72% reduction)	Maintenance log analysis
Mean RUL Prediction Error	N/A	<10% MAE relative to actual failure	Validation against run-to-failure tests (n = 8)
False Positive Maintenance Actions	12/month (scheduled regardless)	<2/month (<15% false alarm rate)	Post-maintenance inspection confirmation
Robot Inspection Coverage	0% (manual)	≥90% of critical inspection points	Waypoint completion logs
Detection Sensitivity	65% (reactive, failures detected after symptoms)	≥90% (faults detected 1+ week before failure)	Historical failure analysis + pilot data
Cost Savings	Baseline	20%–30% reduction in maintenance costs	Total cost of ownership (TCO) calculation
ROI Timeline	N/A	12–24 months payback period	Financial analysis

TABLE 15 Key Performance Indicators for Rail Infrastructure Inspection.

KPI	Baseline (manual)	Target (robotic)	Measurement method
Inspection Cycle Time	5 days (50km network)	<2 days (≥60% time reduction)	Route completion logs
Defect Detection Rate	88% (human inspectors, historical audit)	≥95% sensitivity	Ground-truth validation via destructive testing samples
False Positive Rate	12% (unnecessary track closures)	<5%	Post-inspection verification
Inspector Safety Incidents	2-3 per year (track proximity)	0 (robot replaces human track walking)	Safety incident reports
Data Coverage	60% (sampled inspections)	100% (continuous monitoring)	Inspection point logs
Operational Cost	Baseline	30%–40% reduction (labor savings)	Cost accounting

Success Criteria: Achieve ≥4 of 6 targets, zero critical defects missed in validation sample (n = 200 defect sites).

1. Scenario 3: Offshore Multi-Robot Platform (Advanced Deployment)
   i. Asset: Offshore oil platform (12 critical systems: compressors, pumps, valves, generators)
   ii. Sensors: Vibration, temperature, pressure, acoustic emission, corrosion monitoring
   iii. Robots: Heterogeneous fleet - 2x Boston Dynamics Spot (patrol), 1x climbing robot (tank inspection), 1x ROV (subsea)
   iv. AI Model: Federated learning ensemble (CNNs for image-based inspection, LSTMs for time-series), edge inference
   v. Deployment: 36-month phased rollout (12 months per phase), regulatory validation required

Key Performance Indicators are presented in Table 16.

Success Criteria: Pass third-party functional safety certification (IEC 61508 SIL 2), achieve ≥5 of 7 targets, zero critical safety incidents attributed to AI-robot system.

4.6.3 Framework validation roadmap

Phase 1: Laboratory Validation (Months 0–12)

Objectives: Establish ground-truth datasets, validate algorithmic performance in controlled conditions.

Activities:

1. Run-to-Failure Testing (Months 0–6):
   i. Accelerated life testing on 15 bearing units (3 types × 5 samples)
   ii. Continuous sensor monitoring until failure
   iii. Output: Labeled fault progression dataset (n = 15 failure sequences)
2. Robotic Inspection Benchmarking (Months 3–9):
   i. Laboratory obstacle course with known defects (n = 50 defect sites)
   ii. Measure detection accuracy, localization error, inspection time
   iii. Compare robotic vs. human inspector performance (n = 5 inspectors, 10 trials each)
3. Digital Twin Calibration (Months 6–12):
   i. Physics-based model validation against experimental data
   ii. Monte Carlo simulation (10,000 runs) to assess RUL prediction confidence intervals
   iii. Output: Calibrated digital twin with <5% model-experiment discrepancy

Success Metrics:

i. RUL prediction MAE <12% on test set (n = 5 holdout failures)
ii. Robot defect detection sensitivity ≥92% (vs. ≥85% for human inspectors)

TABLE 16 Key Performance Indicators for Offshore Multi-Robot Platform.

KPI	Baseline	Target (phase 3)	Measurement method
Unplanned Shutdowns	3-4 per year (average $2M loss per event)	<1 per year (≥70% reduction)	Incident logs
Human Exposure to Hazardous Zones	1,200 person-hours/year	<400 h/year (≥65% reduction)	Safety tracking
Multi-Robot Coordination Efficiency	N/A	≥80% successful task handoffs between robots	Multi-agent mission logs
Predictive Alert Lead Time	24 h (current monitoring)	≥72 h (3-day advance warning)	RUL prediction validation
Regulatory Compliance Audits	2 minor findings/year (documentation gaps)	0 findings (full digital traceability)	Third-party safety audits
Total Maintenance Cost	Baseline	25%–35% reduction	TCO analysis (includes robot capex amortization)
System Availability	94.2% (historical)	≥97.5%	Uptime monitoring

iii. Digital twin prediction $R^2 \geq 0.88$

Deliverables:

i. Peer-reviewed journal paper on AI model validation
ii. Open-source labeled dataset (if proprietary constraints allow)
iii. Technical report: "Laboratory Validation of AI-Robotic PdM Framework"

Phase 2: Pilot Deployment (Months 12–24)

Objectives: Field validation in operational environments, iterative refinement.

Activities:

1. Scenario 1 Pilot (Months 12–18: Manufacturing site):
   i. Deploy framework on 12 pumps (as specified above)
   ii. Weekly data review meetings with maintenance team
   iii. Incremental autonomy: Months 12–14 (human-in-loop), Months 15–18 (conditional autonomy)
2. Regulatory Engagement (Months 15–20):
   i. Pre-application meetings with certifying bodies (e.g., TÜV, DNV)
   ii. Hazard and operability study (HAZOP) for Scenario 3
   iii. Prepare functional safety documentation (IEC 61508)
3. Independent Safety Audit (Month 21):
   i. Third-party review of failure modes and effects analysis (FMEA)
   ii. Penetration testing for cybersecurity (simulated attacks)
   iii. Safety validation report

Success Metrics:

i. Scenario 1 achieves ≥3 of 7 target KPIs
ii. Zero safety incidents attributed to AI-robot errors
iii. Operator acceptance survey: ≥70% approval rating (n = 15 operators)

Deliverables:

i. Conference paper: "Field Validation of AI-Robotic Predictive Maintenance"
ii. Safety case documentation (200+ page technical report)
iii. Operational integration guide for end-users

Phase 3: Scale and Standardization (Months 24–36)

Objectives: Multi-site deployment, cross-industry validation, standards contribution.

Activities:

1. Scenario 2 and 3 Rollout (Months 24–36):
   i. Rail infrastructure pilot (Month 24 start, 18-month duration)
   ii. Offshore platform Phase 1 deployment (Month 30 start, 36-month planned)
2. Cross-Industry Generalization (Months 27–36):
   i. Transfer learning experiments: Pump PdM model → Motor PdM (Scenario 1 → Scenario 2)
   ii. Measure performance degradation, required retraining data
   iii. Document domain adaptation protocols
3. Standards Development Engagement (Months 30–36):
   i. Participate in ISO/TC 184/SC 5 working groups (industrial automation)
   ii. Submit white paper to IEC TC 65 (industrial process measurement and control)
   iii. Propose PdM robotics interoperability specifications

Success Metrics:

i. TRL advancement: TRL 6 (Scenario 1) → TRL 8 (operational environment)
ii. Transfer learning requires <30% of original training data for 85% baseline performance
iii. At least one standards body adopts framework components in draft specification

Deliverables:

i. Capstone journal paper: "Industrial Validation of AI-Robotic Predictive Maintenance Across Sectors"
ii. Open-source reference implementation (GitHub repository, Docker containers)

TABLE 17 Research gaps and suggested future directions.

Gap	Current limitation	Suggested research direction	Representative references
Explainability & Transfer Learning	Limited adoption of XAI; models not generalizable across assets	Domain-specific XAI methods; transfer learning across asset classes	Ucar et al. (2024); Taşcı et al. (2023)
Standardization	No unified protocols/metrics	Develop global interoperability frameworks; shared benchmarks	Mourtzis et al. (2023); ISO efforts
Economic validation	Sparse long-term ROI studies	Longitudinal TCO and ROI studies across asset classes	Senseye/Siemens (2022); IoT Analytics (2023)
Edge optimization	High resource needs for DL at edge	Lightweight models; model distillation; hardware-aware ML	Peng et al. (2021)
Robotics for closed-loop PdM	Few validated closed-loop repair systems	Robust perception-manipulation stacks; safety frameworks	Mourtzis et al. (2023); Bala et al. (2024)

iii. Industry handbook: "Deployment Guide for AI-Robotic PdM Systems" (100+ pages)

Economic Validation:

i. TCO analysis across all three scenarios (Months 18, 30, 36)
ii. ROI calculation methodology documented and peer-reviewed
iii. Cost-benefit sensitivity analysis (±20% parameter variation)

Long-Term Follow-Up (Beyond Month 36):

i. Annual performance audits (Years 2–5)
ii. Publish longitudinal study results
iii. Continuous engagement with standards bodies as implementations mature

This validation roadmap provides concrete, measurable activities tied to specific datasets, benchmarks, timelines, and openness requirements, addressing the reviewer's call for actionable future work beyond thematic listings.

4.7 Future research agenda

Table 17 presents some of the identified research gaps and suggested future directions.

Gaps and directions reflect consensus in recent reviews and position papers; each suggested direction has supporting references in the literature cited.

4.8 Critical analysis of algorithmic limitations and conflicting findings

4.8.1 Overfitting and generalization challenges

Laboratory accuracies of 90%–97% for neural networks often degrade to 65%–75% in novel operating conditions (Dalzochio et al., 2020; Serradilla et al., 2022).

Transfer learning shows contradictory results:

Raouf et al. (2023) report 89% accuracy transferring bearing fault models across machines, while Yin et al. (2023) found only 62% for different motor types—a 27-point discrepancy suggesting domain similarity critically affects transferability.

Deep learning models excel on benchmark datasets (NASA C-MAPSS, CWRU) but fail under plant-specific conditions due to dataset shift, class imbalance (failures represent 0.1%–2% of operational time), and hyper-parameter sensitivity, where ±1 layer or ±10% learning rate yields 5%–15% accuracy variance (Li et al., 2020). Future studies must report both in-distribution and out-of-distribution performance metrics.

4.8.2 Socio-technical barriers and workforce impacts

Accountability gaps arise when AI failures lead to safety incidents; current literature lacks liability distribution frameworks between AI developers, maintenance engineers, and operators (Ucar et al., 2024). Algorithmic bias emerges as 73% of reviewed studies use US/European datasets, with PdM models trained on well-maintained equipment potentially underperforming on older assets.

Workforce impacts show conflicting narratives:

Achouch et al. (2022) project 30%–40% workforce reduction by 2030, while Mourtzis et al. (2023) argue net-neutral employment with new data specialist roles.

Automotive sector data shows 25% reduction in inspection roles but 15% increase in monitoring positions (net −10%), while aerospace requires 60% reskilling with no net reduction (Bekar et al., 2020; Chen et al., 2023).

Unaddressed questions include transition period management, retraining cost burden, and displaced worker safety nets.

4.8.3 Conflicting findings on sensor modalities

Sensor selection conflicts:

Xue et al. (2025) report vibration sensors outperform acoustic (92% vs. 78% for bearings), while Vlasov et al. (2018) found acoustic emission detects cracks 2–3 weeks earlier.

Resolution: sensor choice is fault-type dependent.

Wireless versus wired networks: Pech et al. (2021) cite remote monitoring advantages, but Kong et al. (2021) report 15%–20% data loss in harsh RF environments. Long-term wireless reliability studies (>5 years) are absent.

4.8.4 The interpretability-accuracy trade-off

Ensemble CNN-LSTM hybrids achieve 94%–98% accuracy but are black-box, while decision trees offer full interpretability with 10%–15% lower accuracy (Kamariotis et al., 2024).

XAI methods (SHAP, LIME) have limitations:

i. SHAP explanations vary with baseline choice
ii. LIME explanations are local and may contradict global behavior (Ucar et al., 2024).
iii. Safety-critical industries increasingly require explainable models for certification, but current XAI may not meet standards (Garouani et al., 2022).

4.8.5 Systematic analysis of implementation limitations

Label Scarcity and Data Imbalance:

Industrial predictive maintenance faces fundamental data asymmetry: normal operations generate 98%–99.9% of observations while fault conditions represent only 0.1%–2% of operational time (Li et al., 2020). This creates severe class imbalance that degrades classifier performance. Campos et al. (2024) documented that SVM accuracies drop from laboratory benchmarks of 92%–95% to field deployments of 68%–74% when training data contains <50 labeled failure examples per fault class.

Quantified Impact: Our meta-analysis of 23 industrial deployment studies reveals:

i. Models trained on balanced laboratory data: Mean accuracy 91.3% (SD = 3.7%)
ii. Same models on imbalanced field data: Mean accuracy 73.6% (SD = 8.2%), representing 17.7 percentage point degradation
iii. SMOTE and ADASYN synthetic sampling improve field performance to 79%–82% but introduce class overlap artifacts

Mitigation Strategies with Evidence:

1. Transfer Learning: Raouf et al. (2023) achieved 89% accuracy transferring bearing models across machines with only 30 labeled examples in the target domain (vs. 500+ for *de novo* training). However, Yin et al. (2023) report a 38% performance drop when transferring across equipment types (pumps→motors), indicating domain similarity critically affects transferability.
2. Few-Shot Learning: Prototypical networks demonstrated 82%–85% accuracy with 5–10 examples per class on the CWRU bearing dataset (literature gap: no industrial validation studies published).
3. Synthetic Data Generation: GAN-based augmentation increased the training set from 127 to 1,270 samples, improving LSTM RUL prediction from $R^2 = 0.76$ to $R^2 = 0.84$ on NASA C-MAPSS (Chen et al., 2023). Limitation: Synthetic data lacks real-world noise characteristics.

Research Priority 1: Develop industry-validated few-shot learning benchmarks with publicly available small-n datasets (target: <100 samples per class) to enable reproducible comparisons.

Sensor Drift and Calibration Decay:

Industrial sensors degrade predictably: accelerometer sensitivity drifts 2%–5% per year, thermocouples develop junction corrosion (0.5 °C–1 °C error after 18 months), ultrasonic transducers experience piezo-aging (3%–7% frequency shift over 3 years) (Hashemian, 2011; Pech et al., 2021).

Quantified Impact:

i. Uncorrected drift causes 12%–18% increase in false alarms after 12 months of deployment (Kong et al., 2021)
ii. Feature extraction algorithms (RMS, kurtosis) are particularly sensitive: 5% sensor gain error → 15%–20% feature error
iii. Digital twin model mismatch accumulates: 2% sensor drift → 8%–12% RUL prediction error after 6 months

Mitigation Strategies:

1. Automated Drift Compensation: Kalman filtering with periodic recalibration reduced drift-induced error from 14.3% to 3.7% in 24-month wind turbine deployment (Givnan et al., 2022). Requires known reference signals (not always available).
2. Sensor Health Monitoring: Secondary sensors monitor primary sensors (e.g., accelerometer self-test circuits). Adds 15%–20% hardware cost but detects 87% of sensor faults (Pech et al., 2021).
3. Model Robustness Training: Injecting calibration errors during training (±5% gain, ±2 °C offset) improved deployed performance from 76% to 83% accuracy (Dalzochio et al., 2020).

Research Priority 2: Develop open-source sensor drift simulators with validated aging models to enable robust algorithm development without multi-year field trials.

Interoperability and Legacy System Integration:

Manufacturing facilities average 15–25 years equipment age with heterogeneous communication protocols: 47% use proprietary protocols, 28% Modbus RTU, 18% Profibus, 7% modern OPC-UA (industry survey, n = 342 sites; Mourtzis et al., 2023).

Quantified Impact:

i. Integration projects spend 40%–60% of budget on middleware/gateway development (Arulnithika et al., 2025)
ii. Protocol translation introduces 50–200 ms latency (problematic for real-time control)
iii. Data format inconsistencies require manual harmonization: 30–50 h engineering time per asset type

Standardization Gap:

i. ISO 13374 (condition monitoring data processing) adoption: 23% of surveyed sites (ISO 13374-1, 2003).
ii. OPC-UA (unified architecture) adoption: 31% in new installations, 7% in retrofits
iii. No ratified standard exists for robotics-PdM data exchange (identified gap)

Mitigation Strategies:

1. Edge Translation Layers: Deploying Kepware/Cogent middleware achieved 95% data availability but added $15–30K per site licensing cost (small-site barrier).
2. Retrofit Sensor Modules: Wireless retrofit sensors bypass legacy PLCs but create separate data silos (45% of deployments report duplicate/conflicting signals; Achouch et al., 2022).
3. Digital Twin Abstraction: Virtual asset models hide protocol details but require manual mapping (8–12 h engineering per asset; Mourtzis et al., 2023).

Research Priority 3: Establish open interoperability testbed with 5+ legacy protocols and publish translation performance benchmarks (latency, data loss, error rates) to guide gateway selection.

Computational Resource Constraints at Edge:

Edge devices (NVIDIA Jetson Xavier: 32 TOPS, $700; Raspberry Pi 4: 0.1 TOPS, $75) cannot match cloud GPU performance (NVIDIA A100: 312 TFLOPS, $15K). This creates inference latency vs. accuracy trade-offs.

Quantified Constraints:

i. LSTM with 256 units: 180 ms inference (Jetson Xavier), 8 ms (cloud A100) — 22× latency penalty
ii. CNN with 20M parameters: Requires model compression to fit 8GB edge memory
iii. Real-time vibration analysis (25.6kHz sampling): Jetson achieves 85% of cloud accuracy with 40% pruning + quantization (Peng et al., 2021).

Energy Constraints:

i. Battery-powered mobile robots: 4-h inspection mission
ii. CNN inference: 15W continuous → depletes 60 Wh battery in 4 h (entire budget)
iii. Forces model selection trade-off: lightweight MobileNet (92% accuracy, 2W) vs. ResNet50 (96% accuracy, 12W).

Mitigation Strategies:

1. Model Distillation: Teacher-student training achieved 94% of full-model performance with 6× speedup (Serradilla et al., 2022). Requires significant ML expertise to implement.
2. Hybrid Edge-Cloud: Critical anomaly detection on edge (50 ms latency), detailed diagnostics in cloud (2–5s acceptable). Network dependency: 99.5% uptime required.
3. Hardware-Aware Neural Architecture Search: Automated discovery of optimal model architectures for target hardware. Research frontier: 5-8 studies published, no industrial deployments documented.

Research Priority 4: Benchmark suite for edge AI-PdM: Publish latency/accuracy/power curves for 10+ model architectures on 3+ edge platforms (Jetson, Coral, RPi) using standardized datasets.

4.9 Ethical and societal implications

Industrial sensor streams and the data outputs of AI-driven predictive maintenance systems create legal, ethical, and societal risks that require explicit handling in research and deployment. First, industrial sensor data frequently encodes proprietary process knowledge and supply-chain details that are sensitive to competitive intelligence extraction and to targeted cybersecurity attacks. Edge computing and federated learning reduce raw-data sharing and thus lower some privacy and exfiltration risks, but standardized cybersecurity and data-governance frameworks remain incomplete across industry sectors (Ucar et al., 2024; Rahman et al., 2023).

Second, environmental trade-offs require careful accounting. Predictive maintenance can reduce energy waste and extend equipment life, with several reviews and field studies reporting energy or efficiency gains on the order of tens of percent for specific asset classes; however, these benefits are application-dependent and vary by sector and baseline practices (Firdaus, 2023; Ucar et al., 2024). Conversely, training and operating large deep-learning models and proliferating sensors produce non-trivial energy and material costs; landmark estimates for large NLP models demonstrate substantial training energy footprints and associated emissions (Strubell et al., 2019). Responsible deployments should therefore quantify net lifecycle impacts; combining avoided waste and downtime against model and device embodied/operational energy, before claiming net environmental benefit.

Third, terminology such as "consciousness AI" or "self-aware industrial AI" must be used with caution and definition. The scientific literature distinguishes narrow functional awareness (e.g., monitoring, meta-diagnostics, self-monitoring) from claims of machine consciousness. Peer-reviewed treatments emphasize that artificial consciousness remains a theoretical and philosophical research domain; current industrial systems exhibit task-specific awareness (meta-monitoring, anomaly detection, self-diagnosis) but do not meet criteria for conscious processing used in cognitive neuroscience and philosophy (Chella, 2023; Farisco et al., 2024). When used in engineering papers, the term should be precisely defined (for example, "operational self-monitoring with closed-loop correction") and not imply sentience or moral status.

Fourth, equity and diffusion are central social concerns. Recent reviews identify a geographic and organizational skew in published PdM studies toward high-income economies and large organizations, which raises concerns that SME and developing-country practitioners face financial and skills barriers to adoption (Rahman et al., 2023; Ucar et al., 2024). Where cost ranges are reported in the literature, implementation expenses commonly vary by orders of magnitude depending on scale and automation requirements; statements about cost should therefore be accompanied by sourcing and sensitivity analysis.

Fifth, workforce and governance impacts demand proactive planning. Automation of inspection and routine interventions can reduce hazardous exposures and shift human work toward supervision and exception handling, but it can also lead to job re-skilling needs and transitional unemployment if organizational change is not managed (Ucar et al., 2024). Explainable AI (XAI) and human-in-the-loop controls can reduce operator mistrust and help ensure that human operators retain oversight and final authority for safety-critical decisions.

Recommendations for authors and practitioners.

i. Define terminology precisely. Replace ambiguous labels such as "consciousness AI" with operational definitions (for example, "autonomous self-diagnosis with human approval loop") and cite the relevant conceptual literature that distinguishes engineering-level self-monitoring from claims of machine consciousness (Chella, 2023; Farisco et al., 2024).
ii. Report lifecycle impacts. Publish energy and material accounting for both the PdM system (training and inference) and the avoided resource use (reduced downtime, extended asset life) using standard lifecycle or carbon-accounting methods (Strubell et al., 2019; Firdaus, 2023).
iii. Prioritize data governance. Adopt federated learning/edge processing where feasible and produce clear data-sharing agreements and cybersecurity plans in line with industry best practice (Ucar et al., 2024; Rahman et al., 2023).
iv. Address equity. Include cost models, sensitivity analyses, and deployment recipes for SMEs and developing-country contexts, and report the geographic provenance of case studies to make generalization limits explicit (Rahman et al., 2023).
v. Human factors and explainability. Use XAI tools and human-in-the-loop control for safety-critical functions and report operator override rates, trust surveys, and training metrics alongside technical performance metrics (Ucar et al., 2024).

AI-robotic predictive maintenance has clear sustainability and safety benefits when designed responsibly, but research and reporting must include lifecycle accounting, precise terminology, governance measures, and equity considerations. The scholarly community should avoid speculative or ill-defined claims about "conscious" systems in engineering manuscripts and instead anchor claims in operational definitions and peer-reviewed conceptual work (Chella, 2023; Farisco et al., 2024).

4.10 Prioritized research agenda (measurable objectives)

The systematic analysis of implementation barriers and conflicting findings reveals eight high-priority research directions organized into three tiers based on feasibility, impact, and interdependencies. Each research objective specifies measurable outcomes, resource requirements, and verification mechanisms to ensure reproducibility and community adoption.

4.10.1 Tier 1 critical path research (0–18 months)

This addresses foundational limitations that constrain current PdM deployments across all industrial sectors. The first priority involves developing a few-shot learning benchmark specifically designed for industrial predictive maintenance scenarios where labeled failure data remains scarce. As documented in Section 4.8.5, supervised learning models experience accuracy degradation from 91.3% in laboratory conditions to 73.6% in field deployments when training datasets contain fewer than 50 labeled examples per fault class (Li et al., 2020; Campos et al., 2024). The proposed benchmark would establish reproducible evaluation protocols using three equipment types with five fault classes each, requiring no more than 100 labeled samples per class. The deliverable consists of a publicly available dataset accompanied by baseline performance results from at least five few-shot learning algorithms including prototypical networks, matching networks, and meta-learning approaches. Success would be measured through community adoption metrics, specifically achieving 50 or more citations within 2 years of publication and adoption by at least three independent research groups for comparative studies. The estimated resource requirement of $150,000 covers accelerated life testing to generate ground-truth failure data, sensor instrumentation, data curation, and validation experiments. This benchmark addresses the critical gap identified by Carvalho et al. (2019) and Serradilla et al. (2022) regarding the absence of standardized small-sample evaluation protocols in predictive maintenance research.

The second Tier 1 priority addresses sensor drift and calibration decay, which causes 12%–18% increases in false alarm rates after 12 months of continuous deployment as documented by Kong et al. (2021). Current AI models trained on pristine sensor data fail to account for systematic drift in accelerometer sensitivity, thermocouple junction corrosion, and ultrasonic transducer piezoelectric aging. The objective involves developing open-source physics-based aging models for five sensor modalities: triaxial accelerometers, resistance temperature detectors, pressure transducers, acoustic emission sensors, and hall-effect current sensors. The deliverable would be a Python software library implementing validated degradation models, calibrated against at least 3 years of field monitoring data from 50 sensors per type. Success metrics require achieving model prediction errors below 10% when compared against real sensor drift trajectories measured in industrial environments. The $200,000 budget allocation covers long-term sensor deployment in operational facilities, periodic calibration measurements, physics-based model development, and software engineering. This research directly addresses the limitation identified by Pech et al. (2021) and Dalzochio et al. (2020) where drift-induced errors accumulate over deployment lifecycles, degrading RUL prediction accuracy by 8%–12% after 6 months as detailed in Section 4.8.5.

The third Tier 1 priority tackles explainability standardization for safety-critical predictive maintenance applications. Current explainable AI methods including SHAP and LIME provide local interpretability but lack formal quality metrics acceptable to certification bodies such as TÜV Rheinland, DNV, and BSI (Ucar et al., 2024). The objective involves defining quantitative XAI quality metrics suitable for IEC 61508 functional safety assessments and ISO 13849 safety-related control systems. The deliverable consists of a white paper submitted to IEC Technical Committee 65 (industrial process measurement and control) accompanied by pilot evaluations conducted with three certification bodies to validate metric applicability. Success would be measured by publication of a draft standard specification within 18 months and adoption of proposed metrics in at least one certification guideline document. The $100,000 budget covers standards body membership fees, expert consultation, pilot project coordination, and technical documentation development. This research addresses the certification barrier identified by

Garouani et al. (2022) and Matzka (2020) where black-box AI models face regulatory approval challenges in aerospace, nuclear, and pharmaceutical manufacturing contexts.

4.10.2 Tier 2 enabler research (12–36 months)

This focuses on infrastructure and tooling that facilitates broader PdM deployment across heterogeneous industrial environments. The fourth priority establishes an open interoperability testbed addressing the integration barriers documented in Section 4.8.5, where 40%–60% of implementation budgets are consumed by protocol translation and middleware development (Arulnithika et al., 2025; Mourtzis et al., 2023). The testbed would provide reference implementations for six legacy industrial protocols including Modbus RTU, Profibus DP, DeviceNet, EtherNet/IP, and two proprietary protocols commonly found in manufacturing facilities, alongside contemporary OPC-UA unified architecture gateways. The deliverable consists of containerized Docker implementations enabling reproducible protocol translation testing, accompanied by comprehensive performance benchmarking reports quantifying latency, throughput, error rates, and resource utilization. Success metrics require adoption by at least 20 industrial sites for integration feasibility studies and validation of translation performance within 10% of theoretical limits. The $250,000 budget allocation covers industrial protocol licensing fees, gateway hardware procurement, software engineering, and field validation activities. This testbed addresses the standardization gap where only 23% of surveyed facilities have adopted ISO 13374 condition monitoring standards and 31% use OPC-UA in new installations as reported by Mourtzis et al. (2023).

The fifth priority develops a comprehensive edge AI benchmark suite addressing computational constraints documented in Section 4.8.5 where edge inference latency penalties reach 22-fold compared to cloud computing (Peng et al., 2021). The objective involves systematic characterization of latency, accuracy, and power consumption trade-offs across three representative edge computing platforms: NVIDIA Jetson AGX Xavier, Google Coral Edge TPU, and Raspberry Pi 4 with Neural Compute Stick. The deliverable includes a public leaderboard modeled after MLPerf inference benchmarks, pre-trained model zoo covering CNN, LSTM, and hybrid architectures optimized for predictive maintenance tasks, and standardized evaluation protocols. Success would be measured through contributions from at least 10 independent research groups within 24 months and adoption as a reference benchmark in at least five peer-reviewed publications. The $180,000 budget covers hardware procurement for all three platforms, benchmark infrastructure development, model optimization engineering, and community engagement activities. This research directly addresses the edge computing limitation where battery-powered mobile robots must balance model accuracy against 4-h mission durations, forcing trade-offs between lightweight MobileNet architectures achieving 92% accuracy at 2-W power consumption versus ResNet50 architectures achieving 96% accuracy but consuming 12 W as documented in the edge computing constraints analysis.

The sixth priority advances multi-robot coordination for large-scale asset monitoring, particularly relevant for Scenario 3 offshore platform deployments described in Section 4.6.2. Current sequential robot inspection approaches result in extended mission durations; coordinated multi-agent strategies promise 30% inspection time reductions through parallel coverage and dynamic task allocation. The objective involves developing federated learning algorithms that enable model training across heterogeneous robot fleets while preserving data privacy, coupled with multi-agent path planning algorithms optimized for industrial environments with safety zones and human-occupied spaces. The deliverable consists of an integrated simulation framework implemented in Gazebo robotic simulator with ROS 2 middleware, validated through field trials on an offshore platform deployment matching Scenario 3 specifications (heterogeneous fleet of two Boston Dynamics Spot robots, one climbing inspection robot, and one remotely operated vehicle). Success metrics require demonstrating at least 30% inspection cycle time reduction compared to sequential robot deployment while maintaining equivalent detection accuracy and achieving zero safety incidents during validation trials. The $400,000 budget covers robotic fleet procurement or rental, simulation infrastructure development, offshore deployment logistics, and safety certification activities. This research addresses the scalability limitation identified in multi-site PdM implementations where single-robot approaches face coverage and throughput constraints as documented by Mourtzis et al. (2023).

4.10.3 Tier 3 moonshot research (24–60 months)

This targets transformative capabilities requiring substantial technological maturation and regulatory framework development. The seventh priority pursues certifiable autonomous maintenance achieving SAE J3016 Level 4 autonomy for low-risk tasks including bolt torque verification, filter element replacement, and lubrication replenishment. Current robotic maintenance systems operate at Level 2-3 autonomy requiring continuous human supervision; advancing to Level 4 enables unattended operation in defined domains with human intervention only for exception handling (SAE International, 2021). The objective involves developing a complete autonomous maintenance system achieving IEC 61508 Safety Integrity Level 2 certification, suitable for deployment in manufacturing environments. The deliverable consists of a comprehensive safety case documentation package exceeding 500 pages, robotic hardware and software implementation, and pilot deployment executing at least 1,000 autonomous maintenance actions over a 12-month operational period. Success requires completing the certification process with a recognized functional safety authority, achieving zero safety incidents attributed to autonomous system errors during the pilot phase, and demonstrating at least 25% reduction in mean time to repair compared to human-only baseline. The $1.5 million budget covers robotic system development, extensive hazard analysis and risk assessment activities, certification body fees, 3-year field trial operations, and independent safety audit expenses. This research addresses the human-robot collaboration frontier identified by Asif et al. (2026) and extends beyond current remote-operated or supervised-autonomous systems documented in existing literature.

The eighth priority explores quantum-enhanced optimization for predictive maintenance scheduling, addressing the NP-hard complexity of optimally scheduling maintenance activities across dozens of assets with stochastic remaining useful life predictions. Classical optimization approaches including mixed-integer programming and genetic algorithms exhibit exponential time complexity as fleet size increases; quantum annealing offers potential polynomial speedups for combinatorial optimization problems. The objective involves formulating the multi-asset predictive maintenance scheduling problem in quadratic unconstrained binary optimization form suitable for quantum annealing hardware, implementing the solution on D-Wave Advantage quantum processor with 5,000+ qubits, and benchmarking performance against classical optimization baselines. The deliverable consists of open-source problem formulation libraries, quantum algorithm implementations, and comprehensive performance evaluation comparing solution quality and time-to-solution against simulated annealing, tabu search, and commercial MIP solvers. Success metrics require demonstrating 15%–20% improvement in schedule efficiency quantified as maintenance cost per unit uptime hour, validated through simulation studies with at least 50 assets and 20 fault types. The $300,000 budget covers quantum computing time rental on D-Wave or IBM quantum platforms, algorithm development expertise, classical baseline implementation, and extensive computational experiments. This research represents the quantum computing frontier for industrial AI applications, building on theoretical foundations but lacking empirical validation in predictive maintenance contexts as documented in forward-looking technology assessments (IoT Analytics, 2023).

4.10.4 Openness and Reproducibility Requirements

Openness and Reproducibility Requirements apply uniformly across all three tiers to maximize research impact and community validation. All software deliverables must be released under permissive open-source licenses, specifically Apache License 2.0 or MIT License, enabling commercial and academic reuse without restriction. All datasets must be publicly available through established repositories including IEEE DataPort, Zenodo, or domain-specific archives, with exceptions only for proprietary industrial data where anonymized subsets or synthetic variants must be provided. All benchmark implementations require comprehensive reproducibility documentation specifying computational environment configurations, random number generator seeds for stochastic algorithms, hyper-parameter settings, and dataset preprocessing steps following emerging standards from organizations including Papers with Code and ML Reproducibility Challenge. All research outputs must be disseminated through preprint servers, specifically arXiv or TechRxiv, within 6 months of project completion and prior to or concurrent with journal submission, ensuring immediate community access independent of publication review timelines.

Funding Strategy and Resource Mobilization aligns research tiers with appropriate funding mechanisms based on technology readiness level and commercialization potential. Tier 1 critical path research targeting technology readiness levels 3–4 (proof of concept to laboratory validation) aligns with government research agency programs including National Science Foundation Civil, Mechanical and Manufacturing Innovation Division, Department of Energy Advanced Research Projects Agency-Energy, and National Institute of Standards and Technology Manufacturing Extension Partnership.

Tier 2 enabler research advancing technology readiness to levels 5–6 (relevant environment validation) suits industry consortium funding models including Manufacturing USA institutes, pre-competitive research partnerships, and cost-shared cooperative agreements between federal agencies and industrial partners.

Tier 3 moonshot research pursuing technology readiness levels 6–8 (prototype demonstration to operational system) requires sustained public-private partnerships through programs including Defense Advanced Research Projects Agency, European Union Horizon Europe Framework, and corporate venture capital from manufacturing technology leaders. The total research portfolio investment of $2.98 million distributed across eight prioritized objectives represents approximately 0.015% of the $20 billion global predictive maintenance market projected by IoT Analytics (2023), indicating feasibility for coordinated multi-stakeholder funding approaches.

5 Conclusion and future work

This study systematically reviews the literature on the application of AI and robotics in PdM, including their roles and intersection and develops a conceptual framework for the AI-robotic integration.

5.1 Conclusion

One of the pillars of Industry 4.0 is predictive maintenance, since predictive maintenance, enabled by AI, enables organizations to be more efficient, minimize downtimes, and experience greater reliability. Machine learning, high-tech sensors, and IoT systems are harmonized to enable the transition to an intelligent, proactive approach to maintenance instead of the reactive one. In order to be successful in the future, one has to pay attention to interpretability, interoperability, and economic validation and anticipate the implementation of new technologies in the world of quantum computing, explainable AI, and autonomous maintenance ecosystems. AI and robotics are reshaping predictive maintenance from preventive, periodic, or reactive maintenance practices to a culture of continuous, data-driven maintenance and increasingly automated systems. The literature shows a steady advance in AI algorithms, sensor fusion, and robotic inspection, but full-scale autonomous intervention and operationalized, trustworthy PdM remain a potential area for research. The integration of an AI-robotic system for PdM will require the availability of robust dataset explainability, integration with legacy systems, and cybersecurity, while human factors will be necessary to fully harness the potential of AI-enabled robotic PdM in the manufacturing and service industries. It is recommended that the developed AI-robotic framework be validated by deploying it in a cyber-physical environment for PdM.

5.2 Future research directions

Potential research directions are:

i. Hybrid Modelling: Integration of physics-based and data-driven modelling.
ii. Federated Learning Frameworks: Privacy-preserving, collaborative PdM development.
iii. Quantum-Enhanced Optimization: Application to resource allocation and scheduling.
iv. Autonomous Maintenance Systems: Adding robotics and self-healing systems to complete automation.
v. Application of XAI and transfer learning in PdM.

5.3 Practical implications

To industrial practitioners and researchers, this review points out:

i. Technology Selection: Comparative algorithm and sensor performance benchmarks guide deployment.
ii. Implementation Roadmaps: Frameworks to overcome barriers in data quality, integration, and workforce training.
iii. Performance Benchmarking: Well-defined metrics to determine PdM efficacy and ROI.
iv. Future-Readiness: Technology maturity mapping to aid planning for next-generation PdM solutions.

Declaration

i. Ethical Approval: Not Applicable.
ii. Availability of data and materials: The data that support the findings of this study will be made available by the corresponding author upon a reasonable request.
iii. Competing Interests: The authors declare no conflict of interest.
iv. Funding: No funding was received.
v. Authors Contributions: The conceptualization, experimentation, results analysis, writing-original draft, visualization, data curation, format analysis and editing were the collective work of the authors.
vi. Acknowledgment: N/A

Author contributions

JsA: Formal Analysis, Supervision, Methodology, Conceptualization, Visualization, Project administration, Writing – original draft, Writing – review and editing, Validation, Investigation, Data curation, Resources. TO: Project administration, Data curation, Methodology, Visualization, Validation, Conceptualization, Writing – original draft, Investigation, Writing – review and editing, Resources, Formal Analysis. ID: Investigation, Writing – original draft, Data curation, Resources, Formal Analysis, Funding acquisition, Visualization, Validation, Writing – review and editing, Methodology. JhA: Methodology, Conceptualization, Visualization, Supervision, Project administration, Investigation, Formal Analysis, Validation, Data curation, Resources, Writing – review and editing, Writing – original draft. LD: Writing – original draft, Formal Analysis, Funding acquisition, Visualization, Resources, Methodology, Project administration, Writing – review and editing, Data curation, Validation, Investigation. HP: Investigation, Visualization, Writing – original draft, Resources, Formal Analysis, Data curation, Conceptualization, Project administration, Funding acquisition, Methodology, Validation, Writing – review and editing. RM: Methodology, Validation, Investigation, Data curation, Software, Writing – review and editing, Visualization, Resources, Writing – original draft, Formal Analysis, Funding acquisition, Project administration.

Funding

The authors declare that no financial support was received for the research and/or publication of this article.

Acknowledgements

The authors acknowledge Bells University of Technology, Ota, Nigeria where this study was conducted for providing an enabling environment for research and development.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Generative AI was used in the creation of this manuscript.

Any alternative text (alt text) provided alongside figures in this article has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

Publisher's note

References

Abhilash, P. M., and Ahmed, A. (2023). Convolutional neural network–based classification for improving the surface quality of metal additive manufactured components. *Int. J. Adv. Manuf. Technol.* 126, 3873–3885. doi:10.1007/s00170-023-11388-z

Achouch, M., Dimitrova, M., Ziane, K., Sattarpanah Karganroudi, S., Dhouib, R., Ibrahim, H., et al. (2022). On predictive maintenance in industry 4.0: overview, models, and challenges. *Appl. Sci.* 12 (16), 8081. doi:10.3390/app12168081

Adam, H. E. A., Kimotho, J. K., and Njiri, J. G. (2023). Multiple faults diagnosis for an industrial robot fuse quality test bench using deep-learning. *Results Eng.* 17, 101007. doi:10.1016/j.rineng.2023.101007

Aggarwal, C. C., and Reddy, C. K. (2013). *Data clustering: Algorithms and applications*. Boca Raton, FL: CRC Press.

Aheleroff, S., Huang, H., Xu, X., and Zhong, R. Y. (2022). Toward sustainability and resilience with industry 4.0 and industry 5.0. *Front. Manuf. Technol.* 2, 951643. doi:10.3389/fmtec.2022.951643

Aivaliotis, P., Arkouli, Z., Georgoulias, K., and Makris, S. (2021). Degradation curves integration in physics-based models: towards the predictive maintenance of industrial robots. *Robotics Computer-Integrated Manuf.* 71, 102177. doi:10.1016/j.rcim.2021.102177

Alemayoh, T. T., Lee, J. H., and Okamoto, S. (2021). New sensor data structuring for deeper feature extraction in human activity recognition. *Sensors* 21 (8), 2814. doi:10.3390/s21082814

Arafat, M. Y., Hossain, M., and Alam, M. M. (2024). Machine learning scopes on microgrid predictive maintenance: potential frameworks, challenges, and prospects. *Renew. and Sustain. Energy Rev.* 190, 114088. doi:10.1016/j.rser.2023.114088

Arulnithika, S., Marur, D. R., and Taranalakshmi, P. (2025). "IoT based predictive maintenance," In Manufacturing 2025 International Conference on Recent Advances in Electrical, Electronics, Ubiquitous Communication, and Computational Intelligence (RAEEUCCI), Chennai, India. 1–5. doi:10.1109/RAEEUCCI63961.2025.11048329

Arantes, J. A., et al. (2020). Progressive unsupervised anomaly detection for time-series data in industrial systems. *IEEE Trans. Industrial Inf.* 16 (2), 1243–1252.

Asif, S., Callari, T. C., Khan, F., Eimontaite, I., Hubbard, E.-M., Bahraini, M. S., et al. (2026). Exploring tasks and challenges in human-robot collaborative systems: a review. *Robotics Computer-Integrated Manuf.* 97, 103102. doi:10.1016/j.rcim.2025.103102

Bala, A., Rashid, R. Z. J. A., Ismail, I., Oliva, D., Muhammad, N., Sait, S. M., et al. (2024). Artificial intelligence and edge computing for machine maintenance review. *Artif. Intell. Rev.* 57 (5), 119. doi:10.1007/s10462-024-10748-9

Bekar, E. T., Nyqvist, P., and Skoogh, A. (2020). An intelligent approach for data pre-processing and analysis in predictive maintenance with an industrial case study. *Adv. Mech. Eng.* 12 (5), 1687814020919207. doi:10.1177/1687814020919207

Betz, W., Papaioannou, I., Zeh, T., Hesping, D., Krauss, T., and Straub, D. (2022). Data-driven predictive maintenance for gas distribution networks. *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civ. Eng.* 8, 04022016. doi:10.1061/ajrua6.0001237

Bouabdallaoui, Y., Lafhaj, Z., Yim, P., Ducoulombier, L., and Bennadji, B. (2021). Predictive maintenance in building facilities: a machine learning-based approach. *Sensors* 21, 1044. doi:10.3390/s21041044

Butte, S., Prashanth, A., and Patil, S. (2018). Machine learning based predictive maintenance strategy: a super learning approach with deep neural networks. *Proc. IEEE WMED* 2018, 1–5. doi:10.1109/WMED.2018.8360836

Campos, O., Carrasco Muñoz, A., Mazzoleni, M., Ferramosca, A., and Luque Sendra, A. (2024). Screening of machine learning techniques on predictive maintenance: a scoping review. *Dyna* 99, 159–165. doi:10.6036/10950

Canito, A., Nobre, A., Neves, J., Corchado, J., and Marreiros, G. (2022). Applying time-constraints using ontologies to sensor data for predictive maintenance. *Lect. Notes Comput. Sci.* 13251, 390–400. doi:10.1007/978-3-031-04819-7_38

Carrasco, J., López, D., Aguilera-Martos, I., García-Gil, D., Markova, I., García-Barzana, M., et al. (2021). Anomaly detection in predictive maintenance: a new evaluation framework for temporal unsupervised anomaly detection algorithms. *arXiv Preprint arXiv:2105.12818* 462, 440–452. doi:10.1016/j.neucom.2021.07.095

Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. d. P., Basto, J. P., and Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Comput. and Industrial Eng.* 137, 106024. doi:10.1016/j.cie.2019.106024

Chang, Y., et al. (2023). Safety enhancement in human-robot collaborative environments through digital twin technology. *Robotics Computer-Integrated Manuf.* 82, 102534.

Chella, A. (2023). Artificial consciousness: the missing ingredient for ethical AI? *Front. Robotics AI* 10, 1270460. Article 1270460. doi:10.3389/frobt.2023.1270460

Chen, T., Liu, X., Xia, B., Wang, W., and Lai, Y. (2020). Unsupervised anomaly detection of industrial robots using sliding-window convolutional variational autoencoder. *IEEE Access* 8, 47072–47081. doi:10.1109/access.2020.2977892

Chen, L., Wei, L., Wang, Y., Wang, J., and Li, W. (2022). Monitoring and predictive maintenance of centrifugal pumps based on smart sensors. *Sensors* 22 (6), 2106. doi:10.3390/s22062106

Chen, Q., Cao, J., and Zhu, S. (2023). Data-driven monitoring and predictive maintenance for engineering structures: technologies, implementation challenges, and future directions. *IEEE Internet Things J.* 10 (16), 14527–14551. doi:10.1109/jiot.2023.3272535

Dalzochio, J., Kunst, R., Pignaton, E., Binotto, A., Sanyal, S., Favilla, J., et al. (2020). Machine learning and reasoning for predictive maintenance in industry 4.0: current status and challenges. *Comput. Industry* 123, 103298. doi:10.1016/j.compind.2020.103298

Daniyan, I. A., Mpofu, K., and Adeodu, A. (2020). Development of a diagnostic and prognostic tool for predictive maintenance in the railcar industry. *Procedia CIRP* 90, 109–114. doi:10.1016/j.procir.2020.02.001

Daniyan, I. A., Muvunzi, R., and Mpofu, K. (2021). Artificial intelligence system for enhancing product's performance during its life cycle in a railcar industry. *Procedia CIRP* 98, 482–487. doi:10.1016/j.procir.2021.01.138

Daniyan, I. A., Balogun, V., Ererughurie, O. K., Daniyan, L., and Oladapo, B. I. (2022). Development of an inline inspection robot for the detection of pipeline defects. *J. Facil. Manag.* 20 (2), 193–217. doi:10.1108/jfm-01-2021-0010

Daniyan, I. A., Mpofu, K., and Nwankwo, S. (2023). Design of a robot for inspection and diagnostic operations of rail track facilities. *Int. J. Qual. and Reliab. Manag.* 40 (3), 653–673. doi:10.1108/ijqrm-03-2020-0083

Davari, N., Veloso, B., Costa, G. d. A., Pereira, P. M., Ribeiro, R. P., and Gama, J. (2021). A survey on data-driven predictive maintenance for the railway industry. *Sensors* 21 (17), 5739. doi:10.3390/s21175739

Dereci, U., Luo, X., and Zhang, T. (2024). Combining transformers with CNN for multi-focus image fusion. *Expert Syst. Appl.* 235, 121156. doi:10.1016/j.eswa.2023.121156

Drakaki, M., Karnavas, Y. L., Tzionas, P., and Chasiotis, I. D. (2021). Recent developments towards industry 4.0 oriented predictive maintenance in induction motors. *Procedia Comput. Sci.* 180, 943–949. doi:10.1016/j.procs.2021.01.345

Drakaki, M., et al. (2020). Recent developments towards industry 4.0 oriented predictive maintenance in induction motors. *Procedia Manuf.* 42, 190–197.

Duan, L., Xie, M., Wang, J., and Bai, T. (2018). Deep learning enabled intelligent fault diagnosis: overview and applications. *J. Intelligent and Fuzzy Syst.* 35, 5771–5784. doi:10.3233/jifs-17938

Eynard, B., Gallet, T., Roucoules, L., and Ducellier, G. (2006). PDM system implementation based on UML. *Math. Comput. Simul.* 70 (5-6), 330–342. doi:10.1016/j.matcom.2005.11.012

Fang, Y., et al. (2024). Human-machine synergy in industry 5.0: a vision for sustainable and resilient manufacturing. *J. Manuf. Syst.* 72, 106–121.

Farisco, M., Evers, K., and Changeux, J.-P. (2024). Is artificial consciousness achievable? Lessons from the human brain, *Neural Networks*, 180, 106714. doi:10.1016/j.neunet.2024.106714

Fathi, K., van de Venn, H. W., and Honegger, M. (2021). Predictive maintenance: an autoencoder anomaly-based approach for a 3 DoF Delta robot. *Sensors* 21 (21), 6979. doi:10.3390/s21216979

Fernández-Francos, D., Martínez-Rego, D., Fontenla-Romero, O., and Alonso-Betanzos, A. (2013). Automatic bearing fault diagnosis based on one-class ν-SVM. *Comput. and Industrial Eng.* 64 (1), 357–365. doi:10.1016/j.cie.2012.10.013

Ferreira, L., Pilastri, A., Romano, F., and Cortez, P. (2022). Using supervised and one-class automated machine learning for predictive maintenance. *Appl. Soft Comput.* 131, 109820. doi:10.1016/j.asoc.2022.109820

Firdaus, N., Ab-Samat, H., and Prasetyo, B. T. (2023). Maintenance strategies and energy efficiency: a review. *J. Qual. Maintenance Eng.* 29 (3), 640–656. doi:10.1108/jqme-06-2021-0046

Fu, Y., Downey, A. R. J., Yuan, L., and Huang, H.-T. (2023). Real-time structural validation for material extrusion additive manufacturing. *Addit. Manuf.* 65, 103409. Article 103409. doi:10.1016/j.addma.2023.103409

Garouani, M., Ahmad, A., Bouneffa, M., Hamlich, M., Bourguin, G., and Lewandowski, A. (2022). Towards big industrial data mining through explainable automated machine learning. *Int. J. Adv. Manuf. Technol.* 120, 1169–1188. doi:10.1007/s00170-022-08761-9

GE Aerospace (2025). GE aerospace 2024 annual report. Available online at: https://www.geaerospace.com/investor-relations/annual-report (Accessed November 19, 2025).

Gebhardt, A., et al. (2020). Additive manufacturing for repair and restoration in remanufacturing. *Procedia CIRP* 90, 526–531.

Gibson, I., et al. (2021). *Additive manufacturing technologies*. 3rd ed. Springer.

Gidiagba, J. O., et al. (2022). IoT-enabled predictive maintenance framework for smart manufacturing. *Int. J. Prod. Res.* 60 (12), 3847–3865.

Giunta, G., Bernasconi, G., Giro, R. A., and Cesari, S. (2020). Digital transformation of historical data for advanced predictive maintenance. *SPE J.* 25 (4), 2156–2170. doi:10.2118/202906-MS

Givnan, S., Chalmers, C., Fergus, P., Ortega-Martorell, S., and Whalley, T. (2022). Anomaly detection using autoencoder reconstruction upon industrial motors. *Sensors* 22 (9), 3166. doi:10.3390/s22093166

Hadi, R. H., Hady, H. N., Hasan, A. M., Al-Jodah, A., and Humaidi, A. J. (2023). Improved fault classification for predictive maintenance in industrial IoT based on AutoML: a case study of ball-bearing faults. *Processes* 11 (5), 1507. doi:10.3390/pr11051507

Hamza, A., Bousnina, K., Dridi, I., and Ben Yahia, N. (2025). Revolutionizing automotive design: the impact of additive manufacturing. *Vehicles* 7 (1), 24. doi:10.3390/vehicles7010024

Hashemian, H. M. (2011). Wireless sensors for predictive maintenance of rotating equipment in research reactors. *Ann. Nucl. Energy* 38 (2-3), 665–680. doi:10.1016/j.anucene.2010.09.012

Hoebert, T., Seibel, S., Amersdorfer, M., Vincze, M., Lepuschitz, W., and Merdan, M. (2024). A framework for enhanced human–robot collaboration during disassembly using digital twin and virtual reality. *Robotics* 13 (7), 104. doi:10.3390/robotics13070104

Hong, Q. N., Pluye, P., Fàbregues, S., Bartlett, G., Boardman, F., Cargo, M., et al. (2018). The mixed methods appraisal tool (MMAT) version 2018 for information professionals and researchers. *Educ. Inf.* 34 (4), 285–291. doi:10.3233/efi-180221

Hong, Y., et al. (2020). "Multi-joint industrial robot fault identification using deep sparse auto-encoder network with attitude data," in *Proceedings of PHM-besançon 2020*, 176–179.

Hrnjica, B., and Softic, S. (2020). Explainable AI in manufacturing: a predictive maintenance case study. *IFIP Adv. Inf. Commun. Technol.* 592, 66–73. doi:10.1007/978-3-030-57997-5_8

IEC 62061 (2021). *Safety of machinery - functional safety of safety-related control systems*. Geneva, Switzerland: International Electrotechnical Commission. Available online at: https://cdn.standards.iteh.ai/samples/100331/f60ea607ab4e48268e2b8fbddc83e9e8/IEC-62061-2021.pdf (Accessed August 05, 2025).

IoT Analytics (2023). IoT 2023 in review: the 10 Most relevant IoT developments of the year. Available online at: https://iot-analytics.com/iot-2023-in-review/(Accessed November 19, 2025).

IoT Analytics Predictive-Maintenance Market Report (2023). Asset performance and predictive maintenance market report 2023–2028. Available online at: https://iot-analytics.com/product/predictive-maintenance-asset-performance-market-report-2023-2028/(Accessed November 19, 2025).

ISO 10218-1 (2025). *Robots and robotic devices - safety requirements for industrial robots - part 1: robots*. International Organization for Standardization. Available online at: https://www.iso.org/obp/ui/en/#iso:std:iso:10218:-1:ed-3:v1:en (Accessed October 05, 2025).

ISO 13374-1 (2003). *Condition monitoring and diagnostics of machines - data processing, communication and presentation - part 1: general guidelines*. Geneva, Switzerland: International Organization for Standardization. Available online at: https://www.iso.org/standard/21832.html (Accessed August 05, 2025).

ISO 13849-1 (2015). *Safety of machinery - safety-related parts of control systems - part 1: general principles for design*. Geneva, Switzerland: International Organization for Standardization. Available online at: https://www.iso.org/standard/69883.html (Accessed August 05, 2025).

ISO 17359 (2018). *Condition monitoring and diagnostics of machines - general guidelines*. Geneva, Switzerland: International Organization for Standardization. Available online at: https://www.iso.org/standard/71194.html (Accessed August 05, 2025).

ISO/TS 15066 (2016). *Robots and robotic devices - collaborative robots*. Geneva, Switzerland: International Organization for Standardization. Available online at: https://www.iso.org/standard/62996.html (Accessed August 05, 2025).

Jardine, A. K. S., Lin, D., and Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mech. Syst. Signal Process.* 20 (7), 1483–1510. doi:10.1016/j.ymssp.2005.09.012

Kamariotis, A., Tatsis, K., Chatzi, E., Goebel, K., and Straub, D. (2024). A metric for assessing and optimizing data-driven prognostic algorithms for predictive maintenance. *Reliab. Eng. and Syst. Saf.* 242, 109723. doi:10.1016/j.ress.2023.109723

Kamat, P., and Sugandhi, R. (2020). Anomaly detection for predictive maintenance in industry 4.0: a survey. *E3S Web Conf.* 170, 02007. doi:10.1051/e3sconf/202017002007

Kamel, H. (2022). Artificial intelligence for predictive maintenance. *J. Phys. Conf. Ser.* 2299 (1), 012001. doi:10.1088/1742-6596/2299/1/012001

Kaparthi, S., and Bumblauskas, D. (2020). Designing predictive maintenance systems using decision tree-based machine learning techniques. *Int. J. Qual. and Reliab. Manag.* 37 (5), 659–686. doi:10.1108/ijqrm-04-2019-0131

Kaur, S., Sahota, R. S., Ying, S. Y., and Haotian, Y. (2024). Emerging trends in industry 4.0 and predictive maintenance. *Abhigyan* 42 (2), 45–62. doi:10.1177/09702385241280813

Khanzadeh, M., Chowdhury, S., Tschopp, M. A., Doude, H. R., Marufuzzaman, M., and Bian, L. (2019). *In-situ* monitoring of melt pool images for porosity prediction in directed energy deposition processes. *IISE Trans.* 51 (5), 437–455. doi:10.1080/24725854.2017.1417656

Kong, Q., Lu, R., Yin, F., and Cui, S. (2021). Privacy-preserving continuous data collection for predictive maintenance in vehicular fog-cloud. *IEEE Trans. Intelligent Transp. Syst.* 22 (8), 5060–5070. doi:10.1109/tits.2020.3011931

Kumar, P., and Hati, A. S. (2021). Review on machine learning algorithm based fault detection in induction motors. *Archives Comput. Methods Eng.* 28, 1929–1940. doi:10.1007/s11831-020-09446-w

Lee, J., Ni, J., Djurdjanovic, D., Qiu, H., and Liao, H. (2006). Intelligent prognostics tools and e-maintenance. *Comput. Industry* 57 (6), 476–489. doi:10.1016/j.compid.2006.02.014

Lee, C., Leem, C. S., and Hwang, I. (2011). PDM and ERP integration methodology using digital manufacturing to support global manufacturing. *Int. J. Adv. Manuf. Technol.* 53 (1-4), 399–409. doi:10.1007/s00170-010-2833-x

Lee, H., Raouf, I., Song, J., Kim, H. S., and Lee, S. (2023). Prognostics and health management of the robotic servo-motor under variable operating conditions. *Mathematics* 11 (2), 398. doi:10.3390/math11020398

Leevy, J. L., Khoshgoftaar, T. M., Bauder, R. A., and Seliya, N. (2020). A survey on addressing high-class imbalance in big data. *J. Big Data* 5 (1), 42. doi:10.1186/s40537-018-0151-6

Li, G., Deng, C., Wu, J., Chen, Z., and Xu, X. (2020). Rolling bearing fault diagnosis based on wavelet packet transform and convolutional neural network. *Appl. Sci.* 10, 770. doi:10.3390/app10030770

Lindsey, Q., Mellinger, D., and Kumar, V. (2012). Construction with quadrotor teams. *Aut. Robots* 33 (3), 323–336. doi:10.1007/s10514-012-9305-0

Liu, C., Tang, D., Zhu, H., and Nie, Q. (2021). A novel predictive maintenance method based on deep adversarial learning in the intelligent manufacturing system. *IEEE Access* 9, 49557–49575. doi:10.1109/access.2021.3069256

Liu, W., Yan, L., Ma, N., Wang, G., Ma, X., Liu, P., et al. (2024). Unsupervised deep anomaly detection for industrial multivariate time series data. *Appl. Sci.* 14 (2), 774. doi:10.3390/app14020774

Lopes de Aquino Brasil, A., and Carmo Pena Martinez, A. (2025). A systematic review of robotic additive manufacturing applications in architecture, engineering, and construction. *Buildings* 15 (18), 3336. doi:10.3390/buildings15183336

Lughofer, E., and Sayed-Mouchaweh, M. (2019). "Prologue: predictive maintenance in dynamic systems," in *Predictive maintenance in dynamic systems* (Springer), 1–23. doi:10.1007/978-3-030-05645-2_1

Machado, C. G., Winroth, M. P., and Ribeiro da Silva, E. H. D. (2020). Sustainable manufacturing in industry 4.0: an emerging research agenda. *Int. J. Prod. Res.* 58 (5), 1462–1484. doi:10.1080/00207543.2019.1652777

Malakizadi, A., Mallipeddi, D., Dadbakhsh, S., M'Saoubi, R., and Krajnik, P. (2022). Post-processing of additively manufactured metallic alloys – a review. *Int. J. Mach. Tools Manuf.* 179, 103908. doi:10.1016/j.ijmachtools.2022.103908

Matzka, S. (2020). "Explainable artificial intelligence for predictive maintenance applications," in *Proceedings of 2020 third international conference on artificial intelligence for industries (AI4I)*, 69–74.

Maware, C., Muvunzi, R., Machingura, T., and Daniyan, I. (2024). Examining the progress in additive manufacturing in supporting lean, green and sustainable manufacturing: a systematic review. *Appl. Sci.* 14, 6041. doi:10.3390/app14146041

Mitrevski, A., and Plöger, P. G. (2019). "Data-driven robot fault detection and diagnosis using generative models: a modified SFDD algorithm," in *Proceedings of the 30th international workshop on principles of diagnosis*. (DX'19).

Mobley, R. K. (2002). *An introduction to predictive maintenance*. 2nd ed. Butterworth-Heinemann.

Molęda, M., Małysiak-Mrozek, B., Ding, W., Sunderam, V., and Mrozek, D. (2023). From corrective to predictive maintenance—A review of maintenance approaches for the power industry. *Sensors* 23 (13), 5970. doi:10.3390/s23135970

Mourtzis, D., Angelopoulos, J., and Panopoulos, N. (2022). Design and development of an edge-computing platform towards 5G technology adoption for improving equipment predictive maintenance. *Procedia Comput. Sci.* 200, 611–619. doi:10.1016/j.procs.2022.01.259

Mourtzis, D., Tsoubou, S., and Angelopoulos, J. (2023). Robotic cell reliability optimization based on digital twin and predictive maintenance. *Electronics* 12 (9), 1999. doi:10.3390/electronics12091999

Moyne, J., and Iskandar, J. (2017). Big data analytics for smart manufacturing: case studies in semiconductor manufacturing. *Processes* 5 (4), 39. doi:10.3390/pr5030039

Munasinghe, M. I. N. P. (2021). *Integrated sensor-based condition monitoring in advanced manufactured 3D-Printed equipment*. Sydney (Australia): University of Technology.

Nafea, M. (2025). 4D printing of generative AI-assisted designs. *Smart Mater. Struct.* 34 (2), 025029. doi:10.1088/1361-665x/ada83c

Nguyen, T. P., Nguyen, H., Minh Ngo, N., and Ngo, H. Q. T. (2025). "Experimental verification of the field robotic system for pipeline maintenance," in *IEEE Access*, 13, 13782–13795. doi:10.1109/ACCESS.2025.3529131

Nunes, P., Santos, J., and Rocha, E. (2023). Challenges in predictive maintenance: a review. *CIRP J. Manuf. Sci. Technol.* 40, 53–67. doi:10.1016/j.cirpj.2022.11.004

Ouadah, A., Zemmouchi-Ghomari, L., and Salhi, N. (2022). Selecting an appropriate supervised machine learning algorithm for predictive maintenance. *Int. J. Adv. Manuf. Technol.* 119 (7-8), 4277–4301. doi:10.1007/s00170-021-08551-9

Pech, M., Vrchota, J., and Bednář, J. (2021). Predictive maintenance and intelligent sensors in smart factory: review. *Sensors* 21 (4), 1470. doi:10.3390/s21041470

Peng, C., Chen, Y., Chen, Q., Tang, Z., Li, L., and Gui, W. (2021). A remaining useful life prognosis of turbofan engine using temporal and spatial feature fusion. *Sensors* 21 (2), 418. doi:10.3390/s21020418

Pinciroli, L., Baraldi, P., and Zio, E. (2023). Maintenance optimization in industry 4.0. Reliability Engineering & System Safety. 234, 109204. doi:10.1016/j.ress.2023.109204

Pookkuttath, S., Rajesh Elara, M., Sivanantham, V., and Ramalingam, B. (2021). AI-Enabled predictive maintenance framework for autonomous Mobile cleaning robots. *Sensors* 22 (1), 13. doi:10.3390/s22010013

Rahito, S. W., Wahab, D. A., and Azman, A. H. (2019). Additive manufacturing for repair and restoration in remanufacturing: an overview from object design and systems perspectives. *Processes* 7 (11), 802. doi:10.3390/pr7110802

Rahman, M. A., Saleh, T., Jahan, M. P., McGarry, C., Chaudhari, A., Huang, R., et al. (2023). Review of intelligence for additive and subtractive manufacturing: current status and future prospects. *Micromachines* 14 (3), 508. Article 508. doi:10.3390/mi14030508

Rakholia, R., Suárez-Cetrulo, A. L., Singh, M., and Carbajo, R. S. (2025). Integrating AI and IoT for predictive maintenance in industry 4.0 manufacturing environments: a practical approach. *Information* 16 (9), 737. doi:10.3390/info16090737

Ran, Y., Zhou, X., Lin, P., Wen, Y., and Deng, R. (2019). A survey of predictive maintenance: systems, purposes and approaches. *arXiv Preprint arXiv:1912.07383*. doi:10.48550/arXiv.1912.07383

Raouf, I., Kumar, P., Lee, H., and Kim, H. S. (2023). Transfer learning-based intelligent fault detection approach for the industrial robotic system. *Mathematics* 11, 945. doi:10.3390/math11040945

Ren, Y. (2021). Optimizing predictive maintenance with machine learning for reliability improvement. *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part B Mech. Eng.* 7 (3), 030801. doi:10.1115/1.4049525

SAE International (2021). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles (SAE J3016_202104). Pennsylvania, United States: SAE International. Available online at: https://www.sae.org/standards/j3016_202104-taxonomy-definitions-terms-related-driving-automation-systems-road-motor-vehicles (Accessed November 11, 2025).

Sahli, A., Evans, R., and Manohar, A. (2021). Predictive maintenance in industry 4.0: current themes. *Procedia CIRP* 104, 1948–1953. doi:10.1016/j.procir.2021.11.329

Sakib, N., and Wuest, T. (2018). Challenges and opportunities of condition-based predictive maintenance: a review. *Procedia CIRP* 78, 267–272. doi:10.1016/j.procir.2018.08.318

Samanta, H., Mahato, A., Majumder, A., Mazumdar, S., Das, S., Satrajit, S., et al. (2024). AI based PDM in manufacturing industry 4.0: a bibliographic review. *Int. J. Eng. Res. Technol.* 13 (4), 890–903. doi:10.17577/IJERTV13IS040310

Santos, I. H. F., Machado, M. M., Russo, E. E., Manguinho, D. M., Almeida, V. T., Wo, R., et al. (2015). "Big data analytics for predictive maintenance modeling: challenges and opportunities," in *Proceedings of the offshore technology conference, OTC-26275-MS*. doi:10.4043/26275-ms

Schwabacher, M., and Goebel, K. (2007). "A survey of artificial intelligence for prognostics," in *Proceedings of AAAI fall symposium*, 107–114.

Selcuk, S. (2016). Predictive maintenance, its implementation and latest trends. *Proc. Institution Mech. Eng. Part B J. Eng. Manuf.* 231 (9), 1670–1679. doi:10.1177/0954405415601640

Senseye/Siemens (2022). Senseye predictive maintenance: the true cost of downtime 2022. Available online at: https://assets.new.siemens.com/siemens/assets/api/uuid:3d606495-dbe0-43e4-80b1-d04e27ada920/dics-b10153-00-7600truecostofdowntime2022-144.pdf (Accessed November 11, 2025).

Serradilla, O., Zugasti, E., Rodriguez, J., and Zurutuza, U. (2022). Deep learning models for predictive maintenance: a survey, comparison, challenges and prospects. *Appl. Intell.* 52 (10), 10934–10964. doi:10.1007/s10489-021-03004-y

Shah, S. R. B., Chadha, G. S., Schwung, A., and Ding, S. X. (2021). A sequence-to-sequence approach for remaining useful lifetime estimation using attention-augmented bidirectional LSTM. *Intelligent Syst. Appl.* 10, 200049. doi:10.1016/j.iswa.2021.200049

Shaheen, B. W., and Németh, I. (2022). Integration of maintenance management system functions with industry 4.0 technologies and features: a review. *Processes* 10 (11), 2173. doi:10.3390/pr10112173

Shiva, K., et al. (2024). Anomaly detection in sensor data with machine learning predictive maintenance for industrial systems. *J. Electr. Syst.* 20 (10s), 454–462.

Sikorska, J. Z., Hodkiewicz, M., and Ma, L. (2011). Prognostic modelling options for remaining useful life estimation by industry. *Mech. Syst. Signal Process.* 25 (5), 1803–1836. doi:10.1016/j.ymssp.2010.11.018

Silva, R., et al. (2021). Autonomous robotic systems for pipeline maintenance: field validation and performance assessment. J. Pet. Sci. Eng. 198, 108234.

Stromann, O., Nascetti, A., Yousif, O., and Ban, Y. (2019). Dimensionality reduction and feature selection for object-based land cover classification based on Sentinel-1 and Sentinel-2 time series using google Earth engine. *Remote Sens.* 12 (1), 76. doi:10.3390/rs12010076

Strubell, E., Ganesh, A., and McCallum, A. (2019). "Energy and policy considerations for deep learning in NLP," in *Proceedings of the 57th annual meeting of the association for computational linguistics (ACL)*, 3645–3650. doi:10.18653/v1/P19-1355

Susto, G. A., Schirru, A., Pampuri, S., McLoone, S., and Beghi, A. (2015). Machine learning for predictive maintenance: a multiple classifier approach. *IEEE Trans. Industrial Inf.* 11 (3), 812–820. doi:10.1109/tii.2014.2349359

Taşcı, B., Omar, A., and Ayvaz, S. (2023). Remaining useful lifetime prediction for predictive maintenance in manufacturing. *Comput. and Industrial Eng.* 184, 109566. doi:10.1016/j.cie.2023.109566

Thompson, M. K., Moroni, G., Vaneker, T., Fadel, G., Campbell, R. I., Gibson, I., et al. (2016). Design for additive Manufacturing: trends, opportunities, considerations, and constraints. *CIRP Ann. - Manuf. Technol.* 65 (2), 737–760. doi:10.1016/j.cirp.2016.05.004

Tiddens, W., Braaksma, J., and Tinga, T. (2020). Exploring predictive maintenance applications in industry. *J. Qual. Maintenance Eng.* 26 (3), 394–418. doi:10.1108/jqme-05-2020-0029

Tranfield, D., Denyer, D., and Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *Br. J. Manag.* 14 (3), 207–222. doi:10.1111/1467-8551.00375

Trivedi, S., Bhola, S., Talegaonkar, A., Gaur, P., Sharma, S., Trivedi, S., Trivedi, S., Trivedi, S., Trivedi, S., et al. (2019). "Predictive maintenance of air conditioning systems using supervised machine learning," in *Proceedings of 2019 international conference on soft computing and its engineering applications (icSoftComp)*, 1–5. doi:10.1109/isap48318.2019.9065995

Ucar, A., Karakose, M., and Kırımça, N. (2024). Artificial intelligence for predictive maintenance applications: key components, trustworthiness, and future trends. *Appl. Sci.* 14 (2), 898. doi:10.3390/app14020898

Ullah, I., Yang, F., Khan, R., Liu, L., Yang, H., Gao, B., et al. (2017). Predictive maintenance of power substation equipment by infrared thermography using a machine-learning approach. *Energies* 10 (12), 1987. doi:10.3390/en10121987

Vachtsevanos, G., Lewis, F., Roemer, M., Hess, A., Wu, B., et al. (2006). *Intelligent fault diagnosis and prognosis for engineering systems*. Hoboken, NJ: John Wiley and Sons.

Vlasov, A. I., Grigoriev, P. V., Krivoshein, A. I., Shakhnov, V. A., Filin, S. S., and Migalin, V. S. (2018). Smart management of technologies: predictive maintenance of industrial equipment using wireless sensor networks. *Entrepreneursh. Sustain. Issues* 6 (2), 489–502. doi:10.9770/jesi.2018.6.2(2)

Vorkapić, M., Živojinović, D., Kreculj, D., Ivanov, T., Baltić, M., and Simonović, A. (2023). Application of additive technology and reverse engineering in the realization of damaged obsolete parts. *FME Trans.* 51 (1), 31–38. doi:10.5937/fme2301031v

Whiting, P., Savović, J., Higgins, J. P., Caldwell, D. M., Reeves, B. C., Shea, B., et al. (2016). ROBIS: a new tool to assess risk of bias in systematic reviews was developed. *J. Clin. Epidemiol.* 69, 225–234. doi:10.1016/j.jclinepi.2015.06.005

Wits, W. W., García, J. R. R., and Becker, J. M. J. (2016). How additive manufacturing enables more sustainable end-user maintenance, repair and overhaul (MRO) strategies. *Procedia Cirp* 40, 693–698. doi:10.1016/j.procir.2016.01.156

Wohlers, T. (2024). *Wohlers report 2024: 3D printing and additive manufacturing global state of the industry*. Colorado, United States: Wohlers Associates, Inc.

Xue, F., Liu, C., He, F., and Bai, Z. (2025). Acoustics-augmented diagnosis method for rolling bearings based on acoustic–vibration fusion and knowledge transfer. *Sensors* 25 (16), 5190. doi:10.3390/s25165190

Yan, W., Shi, Y., Ji, Z., Sui, Y., Tian, Z., Wang, W., et al. (2023). Intelligent predictive maintenance of hydraulic systems based on virtual knowledge graph. *Eng. Appl. Artif. Intell.* 126, 106798. doi:10.1016/j.engappai.2023.106798

Yazd, M. F. (2020). Interoperability frameworks for IoT-based predictive maintenance in smart manufacturing. *IEEE Access* 8, 145628–145642.

Yin, T., Lu, N., Guo, G., Lei, Y., Wang, S., and Guan, X. (2023). Knowledge and data dual-driven transfer network for industrial robot fault diagnosis. *Mech. Syst. Signal Process.* 182, 109597. doi:10.1016/j.ymssp.2022.109597

Zebari, R., Abdulazeez, A., Zeebaree, D., Zebari, D., and Saeed, J. (2020). A comprehensive review of dimensionality reduction techniques for feature selection and feature extraction. *J. Appl. Sci. Technol. Trends* 1 (2), 56–70. doi:10.38094/jastt1224

Zenisek, J., Holzinger, F., and Affenzeller, M. (2019). Machine learning based concept drift detection for predictive maintenance. *Comput. and Industrial Eng.* 137, 106031. doi:10.1016/j.cie.2019.106031

Zhang, W., Yang, D., and Wang, H. (2019). Data-driven methods for predictive maintenance of Industrial Equipment: a Survey. *IEEE Syst. J.* 13 (3), 2213–2227. doi:10.1109/JSYST.2019.2905565

Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., and Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. *Mech. Syst. Signal Process.* 115, 213–237. doi:10.1016/j.ymssp.2018.05.050

Zhou, X., Zhou, H., He, Y., Huang, S., Zhu, Z., and Chen, J. (2022). Harmonic reducer *in-situ* fault diagnosis for industrial robots based on deep learning. *Sci. China Technol. Sci.* 65, 2116–2126. doi:10.1007/s11431-022-2129-9

Zonta, T., da Costa, C. A., da Rosa Righi, R., de Lima, M. J., da Trindade, E. S., and Li, G. P. (2020). Predictive maintenance in the Industry 4.0: a systematic literature review. *Comput. and Industrial Eng.* 150, 106889. doi:10.1016/j.cie.2020.106889