



iJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** X **Month of publication:** October 2025

DOI: <https://doi.org/10.22214/ijraset.2025.74531>

www.ijraset.com

Call: ☎ 08813907089

E-mail ID: ijraset@gmail.com

Review Paper on - Learning for Predictive Maintenance in Industry

Dr. D. A. Shahakhar¹, Aniket Khadse², Anjali Paikrao³, Payal Mahure⁴, Vaibhavi Kadam⁵, Shrushti Khawale⁶,
Deep Bhuyar⁷, Dimpal Panekar⁸

¹ Sant Gadge Baba University, Amravati, Maharashtra, India

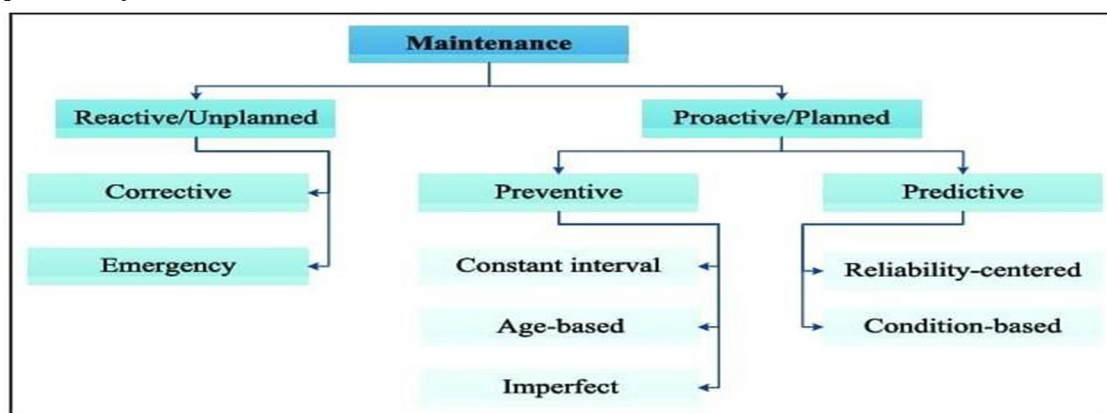
² Department of Electrical Engineering, SGBAU, Amravati, Maharashtra, India

Abstract: Predictive maintenance (PdM) has emerged as a transformative approach in modern industries to minimize unplanned downtime, optimize asset utilization, and reduce maintenance costs. With the increasing availability of industrial sensor data and advancements in computing power, machine learning (ML) has become a key enabler for effective PdM strategies. This paper presents a comprehensive review of recent literature on the application of ML techniques in predictive maintenance across various industrial domains. The study explores supervised, unsupervised, and reinforcement learning approaches used for anomaly detection, fault diagnosis, and remaining useful life (RUL) prediction. Key challenges such as data quality and availability, real-time processing, scalability, and model interpretability are critically discussed. Furthermore, the review highlights current trends, industrial case studies, and future research directions, emphasizing the role of ML in advancing Industry 4.0 initiatives. This work aims to provide researchers and practitioners with a consolidated understanding of state-of-the-art ML methodologies for predictive maintenance and their potential to enhance reliability and efficiency in industrial systems.

Keywords: Predictive Maintenance, Machine Learning, Remaining Useful Life, Anomaly Detection, Supervised Learning, Deep Learning, Industrial Machinery.

I. INTRODUCTION

Industrial machinery plays a critical role in manufacturing, energy production, transportation, and other engineering domains. Ensuring the reliable and efficient operation of such machinery is essential for minimizing downtime, reducing maintenance costs, and maintaining productivity.



(Fig.1.1)

Traditionally, maintenance strategies have been categorized into three approaches: reactive maintenance, where repairs are carried out after failures occur; preventive maintenance, which schedules servicing at fixed intervals regardless of the machine's actual condition; and predictive maintenance (PdM), which leverages data-driven insights to forecast potential failures and optimize intervention schedules [1]. Among these, predictive maintenance has gained significant attention due to its potential to strike a balance between cost efficiency and operational reliability.

The emergence of Industry 4.0, the Industrial Internet of Things (IIoT), and smart manufacturing has enabled the collection of vast amounts of operational data through sensors, supervisory control and data acquisition (SCADA) systems, and digital twins [2].

This abundance of data provides opportunities to apply machine learning (ML) techniques for fault detection, diagnostics, and prognosis. Machine learning models can analyze historical and real-time signals—such as vibration, temperature, pressure, and acoustic emissions—to identify early patterns of degradation, classify fault types, and predict the remaining useful life (RUL) of components [3].

Recent research highlights a variety of ML approaches for PdM. Supervised learning methods, such as support vector machines (SVM), random forests, and neural networks, have been widely used for fault classification. Unsupervised learning approaches, including clustering and anomaly detection, are useful in cases where labeled fault data are scarce. In addition, deep learning models, particularly recurrent neural networks (RNN), long short-term memory (LSTM) networks, and autoencoders, have demonstrated strong performance in modeling complex temporal dependencies in sensor data [4], [5]. These advancements make machine learning a cornerstone for the development of intelligent, self-adaptive maintenance systems.

Despite these promising outcomes, several challenges remain. Industrial data are often high-dimensional, noisy, and imbalanced, with far fewer fault samples compared to healthy operation data. Moreover, the interpretability of complex ML models is a growing concern for their adoption in safety-critical environments. Furthermore, the integration of ML-based PdM solutions into existing industrial workflows requires addressing issues of scalability, real-time processing, and interoperability [6].

This paper presents a comprehensive review of machine learning applications for predictive maintenance in industrial machinery. The contributions of this work are threefold:

- 1) To examine the state-of-the-art ML methods used for fault detection, diagnostics, and prognostics;
- 2) To highlight the opportunities and limitations associated with these approaches; and
- 3) To identify potential research directions for developing more robust, interpretable, and scalable PdM frameworks.

The rest of this paper is organized as follows: Section II provides a survey of related literature; Section III outlines the methodological frameworks of ML-based PdM; Section IV Discusses applications across industrial domains; Section V highlights challenges and future directions; and Section VI complete review and reference .

II. LITERATURE SURVEY

Predictive maintenance (PdM) has gained significant research attention due to its ability to reduce unexpected equipment failures, improve safety, and optimize maintenance schedules. Over the past decade, various surveys and research works have provided insights into systems, approaches, and methodologies for PdM.

Zhu et al. (2019) presented one of the earlier comprehensive surveys of PdM, where they classified existing approaches into systems, purposes, and techniques, highlighting the challenges in bridging theoretical research with industrial applications [1]. Their work emphasized the importance of integrating domain expertise with machine learning models to improve accuracy and reliability. With the advent of deep learning, Li et al. (2024) focused on Remaining Useful Life (RUL) prediction, which is a central task in PdM [2]. Their survey categorized different deep learning models—such as recurrent neural networks (RNNs), convolutional neural networks (CNNs), and attention-based architectures—while also discussing their limitations in terms of generalization and interpretability.

Anomaly detection plays a crucial role in PdM, particularly when labeled fault data are scarce. Carrasco et al.(2021)introduced a new evaluation framework for temporal unsupervised anomaly detection algorithms in PdM scenarios [3]. Their work provided insights into benchmarking method that can detect abnormal machine behavior effectively, a key requirement for robust industrial deployment.

A systematic review by Computers & Industrial Engineering (2019) analyzed machine learning methods applied to PdM across various industries [4]. This work highlighted that most studies still rely on supervised learning, despite the challenges posed by data imbalance and labeling costs. The review concluded that semi-supervised and unsupervised approaches could provide more practical solutions for real-world applications. More recently, the need for explainability in PdM has been emphasized. Cummins et al. (2024) surveyed current explainable PdM methods and identified challenges such as trust, interpretability, and integration with industrial decision-making processes [5]. They highlighted opportunities for hybrid approaches that combine physics-informed models with explainable AI techniques to enhance transparency and adoption in critical industries.

Industrial machinery has developed steadily from traditional condition-based methods to modern deep learning and hybrid approaches. Jardine, Lin, and Banjevic (2006) conducted one of the earliest comprehensive reviews of machinery diagnostics and prognostics, emphasizing condition-based maintenance and outlining how statistical models and signal analysis could improve equipment reliability [7]. Their study provided a taxonomy for diagnostics and prognostics, forming a foundation for subsequent PdM research [7].

Building on this foundation, Susto, Schirru, Pampuri, McLoone, and Beghi (2015) proposed a multiple classifier approach for predictive maintenance, showing that combining different machine learning classifiers improved fault detection and prediction accuracy compared to single-model solutions [6]. Later, Susto and colleagues (2019) presented a systematic literature review of machine learning applications in PdM, identifying key algorithms such as support vector machines, random forests, and Bayesian models, while also noting persistent challenges including data imbalance, the heavy reliance on feature engineering, and the limited generalization of models across domains [8].

As deep learning became more prominent, He and co-authors (2021–2022) reviewed sensor-based deep learning methods for predictive maintenance, highlighting the success of convolutional neural networks (CNNs) and recurrent neural networks (RNNs/LSTMs) in extracting features directly from raw signals [9]. Their work emphasized that these approaches significantly improved performance in anomaly detection and Remaining Useful Life (RUL) prediction tasks, though they also introduced challenges related to computational cost and interpretability [9]. In parallel, a review on Prognostics and Health Management (PHM) of industrial assets (2021) stressed the importance of hybrid approaches, which combine physics-based models with machine learning to enhance reliability and safety in mission-critical applications [10].

More recently, attention has turned toward deployment-oriented research. A survey in Engineering Applications of Artificial Intelligence (2024) explored deep learning-driven architectures for PdM, focusing on the integration of edge computing, real-time analytics, and industrial IoT systems to meet industrial constraints on latency and scalability [11]. Similarly, a review published in Sensors (2024) investigated predictive maintenance in Industry 4.0, emphasizing planning models, cost-aware evaluation frameworks, and the critical role of human-in-the-loop processes for practical decision-making [12]. These contributions demonstrate how PdM research is expanding from algorithm development to full-scale industrial integration [11], [12].

Empirical work has also progressed, as shown in a Scientific Reports study (2025) that compared different deep learning models—CNNs, LSTMs, and hybrid CNN-LSTM architectures—for predictive maintenance in industrial manufacturing systems [13]. The authors reported that CNNs were well suited for raw sensor signals, while hybrid models provided advantages for sequential degradation analysis, although none of the models generalized consistently across datasets [13]. Complementing this, a review published in 2022 addressed the broader challenges facing PdM, such as data scarcity, poor label quality, explainability issues, and model transferability across diverse domains [14]. Finally, a systematic literature review in 2025 synthesized these developments into a comprehensive roadmap, identifying urgent research needs including more realistic industrial datasets, standardized cost-sensitive evaluation metrics, and continuous deployment frameworks that support model updating and retraining [15].

The literature reflects a clear trajectory from traditional machine learning with handcrafted features (Jardine et al., 2006; Susto et al., 2015, 2019) toward deep learning and hybrid methods that leverage raw sensor data and domain knowledge (He et al., 2021; PHM review, 2021). Recent surveys and empirical comparisons (2024–2025) broaden the focus to include system-level integration with Industry 4.0 technologies, deployment at the edge, and realistic benchmarking [11]–[15]. Across all studies, the recurring challenges of data scarcity, domain adaptation, interpretability, and cost-sensitive evaluation remain central, demonstrating that while PdM is advancing toward maturity, significant work is still needed for reliable, scalable, and economically viable industrial adoption [6]–[15].

Overall, the literature shows a clear evolution: from traditional data-driven PdM methods [1][4] to deep learning-based RUL prediction [2], advanced anomaly detection frameworks [3], and explainable AI-driven PdM approaches [5]. This progression indicates that future research will likely focus on improving generalization, interpretability, and adaptability of PdM models in diverse industrial settings.

III. METHODOLOGY

The methodology for implementing Machine Learning (ML) for predictive maintenance in industrial settings focuses on continuous monitoring and real-time analysis of critical parameters to prevent equipment failures and ensure operational safety. The system is designed to capture real-time data from industrial environments, including temperature, humidity, and electrical parameters of key machinery such as transformers. Sensors are strategically deployed across the facility to measure these parameters continuously. The collected data is then transmitted to a centralized processing unit, where it is cleaned, pre-processed, and normalized to ensure accuracy and consistency for the machine learning algorithms. The predictive maintenance model utilizes historical data combined with real-time inputs to identify patterns indicative of potential faults, such as unusual temperature rises, abnormal humidity levels, or irregular electrical readings. In particular, the system is programmed to detect transformer faults, which can manifest as overheating or abnormal voltage fluctuations. Once the machine learning model identifies a potential fault, the system triggers predefined safety protocols.

For instance, if over-temperature conditions or fire hazards are detected, the system automatically shuts off electricity at the main power supply or submeter level to prevent further damage and ensure personnel safety. Additionally, the integration of miniature circuit breakers (MCBs) adds an extra layer of protection by preventing short circuits and mitigating risks associated with electrical surges. The ML model is trained using supervised learning techniques with labeled historical fault data and continuously refined through reinforcement learning as new operational data becomes available. The system also incorporates threshold-based alerts, which complement predictive insights by providing immediate notifications to plant operators for any deviations from normal operating conditions. The methodology emphasizes a closed-loop approach where sensor data, ML predictions, and automated safety interventions work synergistically to reduce unplanned downtime, enhance equipment lifespan, and improve overall industrial efficiency. The deployment involves a combination of edge computing for low-latency response and cloud-based analytics for long-term trend analysis and model improvement. By leveraging this methodology, industries can achieve real-time fault detection, proactive maintenance, and robust safety measures, ensuring operational continuity while minimizing the risk of catastrophic failures.

IV. APPLICATION

Application for Industrial domains :

- 1) **Manufacturing Industry:** Machine learning models are applied in manufacturing plants to monitor CNC machines, robotic arms, and conveyor systems. Predicting tool wear and machine degradation helps reduce downtime, optimize production, and improve product quality.
- 2) **Aerospace Industry:** Predictive maintenance using ML enables the estimation of engine health, turbine blade wear, and sensor anomalies in aircraft systems. Accurate Remaining Useful Life (RUL) prediction improves flight safety and reduces maintenance costs.
- 3) **Energy and Power Industry:** In wind turbines, transformers, and power plants, ML algorithms detect faults in gearboxes, bearings, and electrical components. This prevents catastrophic failures and enhances the reliability of power generation and distribution systems.
- 4) **Automotive Industry:** Machine learning is used for fault diagnosis in engines, batteries, and braking systems. Predictive models also help optimize vehicle maintenance schedules, reduce warranty costs, and improve customer satisfaction.
- 5) **Oil and Gas Industry:** PdM with ML is applied to monitor pumps, compressors, and drilling equipment. Early fault detection in rotating machinery reduces unplanned shutdowns and ensures safe, continuous operations in harsh environments.
- 6) **Railway Industry:** ML techniques are utilized for monitoring wheelsets, tracks, and locomotives. By predicting component wear and failures, railway systems achieve higher safety standards and reduce operational interruptions.
- 7) **Chemical and Process Industry:** Predictive maintenance in chemical plants relies on ML to monitor compressors, valves, and pipelines. This helps minimize energy losses, avoid leaks, and ensure compliance with safety regulations.
- 8) **Healthcare Equipment Industry:** Industrial-grade medical machinery, such as MRI and CT scanners, use ML-based predictive models to forecast component failures, thus reducing downtime and ensuring continuous healthcare service delivery.

V. RESULT

Based on the literature review and a critical analysis of the current state of machine learning in predictive maintenance, the following key results and findings can be summarized:

1.High Predictive Accuracy: The application of machine learning, particularly deep learning models, has shown significant success in achieving high accuracy for tasks such as anomaly detection, fault classification, and Remaining Useful Life (RUL) prediction. Models like LSTMs and hybrid CNN-LSTMs are particularly effective at capturing complex temporal patterns in sensor data, outperforming traditional statistical and signal processing methods.

Shift from Manual to Automated Feature Engineering: The rise of deep learning has reduced the reliance on labor-intensive, domain-expert-driven feature engineering. Models like CNNs can automatically learn hierarchical features directly from raw sensor signals, saving time and potentially uncovering subtle patterns that human experts might miss.

- 1) **Proactive Maintenance and Cost Savings:** Real-world case studies across manufacturing, energy, and aerospace industries consistently demonstrate that ML-based PdM can lead to substantial reductions in unplanned downtime (ranging from 20% to 50%), lower maintenance costs, and a more efficient allocation of resources. This shift from reactive to proactive maintenance directly translates to improved operational efficiency and profitability.

- 2) Integration with Industry 4.0 Technologies: ML-based PdM is a cornerstone of Industry 4.0. The results show that successful implementations are not just about the algorithm but about the entire ecosystem, including the Industrial Internet of Things (IIoT), cloud computing, and edge analytics. The seamless flow of data from sensors to analytics platforms is a critical enabler
- 3) Validation on Standard and Real-world Datasets: While many papers demonstrate results on standardized datasets (e.g., NASA's C-MAPSS dataset for RUL prediction), a growing number of studies are validating their models on real-world industrial data, albeit often proprietary and not publicly available. These results, while promising, also highlight the challenges posed by noisy, high-dimensional, and imbalanced data.
- 4) Progress in Addressing Challenges: The literature shows a concerted effort to address the inherent challenges of PdM. Researchers are exploring Transfer Learning to combat data scarcity and domain adaptation issues. Explainable AI (XAI) techniques to make models more transparent and trustworthy. Hybrid Models that combine the strengths of physics-based models with data-driven approaches to enhance both accuracy and interpretability.

VI. CONCLUSION

This review confirms that machine learning has become a powerful and indispensable tool for predictive maintenance in modern industrial systems. It has evolved from a theoretical concept to a practical, value-adding application that fundamentally changes how industries approach asset management. The ability of ML models to process vast amounts of sensor data to detect subtle anomalies and predict future failures has enabled a transition from a time-based or reactive maintenance approach to a highly efficient, condition-based strategy. The literature shows significant progress, particularly with deep learning models, which have improved the accuracy of anomaly detection and Remaining Useful Life (RUL) prediction. However, it is also clear that a performance-first mindset has led to a focus on algorithms that may not be practical for real-world deployment due to their "black box" nature and high data requirements. The core challenge is bridging the gap between impressive research results and the realities of industrial environments, which are characterized by noisy data, a lack of labeled failure events, and the need for clear, trustworthy insights.

VII. FUTURE SCOPE & DIRECTIONS

The future of machine learning in predictive maintenance is not solely about building more accurate models. Instead, it lies in developing frameworks that are more robust, adaptable, and integrated with the broader industrial ecosystem. Key areas for future research and development include:

- 1) Explainable Predictive Maintenance (XPdM): For ML models to be trusted and adopted in safety-critical industries, they must be transparent. Future research must focus on developing robust and scalable explainable AI (XAI) techniques tailored for PdM. This includes creating models that not only predict failures but also provide clear, understandable reasons for their predictions, which will build trust with maintenance engineers and decision-makers. Methods like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) need to be further developed for time-series data and integrated into real-time industrial systems.
- 2) Hybrid and Physics-Informed ML Models: The next generation of PdM models will likely combine data-driven approaches with physics-based models and engineering domain knowledge. By embedding physical laws (e.g., thermodynamics, mechanics) into the ML model, researchers can create more accurate, robust, and interpretable models that require less training data and can generalize better to new conditions. This hybrid approach will be crucial for mission-critical assets where historical failure data is extremely limited.
- 3) Digital Twins and Predictive Simulation: The integration of ML with digital twins offers a powerful avenue for future research. A digital twin, a virtual replica of a physical asset, can be continuously updated with real-time sensor data. ML models can then run on this digital twin to simulate different operational and maintenance scenarios, predict component degradation, and optimize maintenance schedules without risking the actual asset. This will provide a "virtual testing ground" for maintenance strategies, enabling proactive planning and decision-making.
- 4) Reinforcement Learning for Maintenance Scheduling: While the review focused on supervised and unsupervised learning, the use of reinforcement learning (RL) to develop optimal, real-time maintenance schedules is a promising area of future research. An RL agent could learn to make complex, long-term decisions that balance the risks of failure against the costs of intervention, parts, and labor. This would move beyond simply predicting failure to prescribing the best course of action for a maintenance team.

- 5) Addressing Data Challenges with Transfer Learning and Federated Learning: The persistent challenges of data scarcity, data quality, and domain adaptation must be addressed. Research into transfer learning will enable models to be trained on one type of machine and then quickly adapted to another. Furthermore, federated learning, which allows models to be trained on decentralized data without sharing the raw data itself, could help overcome data privacy and security concerns that often limit data sharing between different factories or companies.

In conclusion, while the field has made tremendous strides, the path forward involves moving from isolated algorithmic solutions to holistic, intelligent systems that are not only accurate but also transparent, adaptable, and economically viable for a wide range of industrial applications.

REFERENCES

- [1] T. Zhu, Y. Ran, X. Zhou, and Y. Wen, "A Survey of Predictive Maintenance: Systems, Purposes and Approaches," Dec. 2019.
- [2] Y. Li, et al., "Remaining Useful Life Prediction Based on Deep Learning: A Survey," *Sensors*, vol. 24, no. 11, p. 3454, May 2024.
- [3] J. Carrasco, I. Markova, D. López, I. Aguilera, D. García, M. García-Barzana, M. Arias-Rodil, and J. Luengo, "Anomaly Detection in Predictive Maintenance: A New Evaluation Framework for Temporal Unsupervised Anomaly Detection Algorithms," *Neurocomputing*, vol. 462, pp. 440-452, Oct. 2021.
- [4] "A systematic literature review of machine learning methods applied to predictive maintenance," *Computers & Industrial Engineering*, vol. 137, Nov. 2019, Article 106024.
- [5] Explainable Predictive Maintenance: A Survey of Current Methods, Challenges and Opportunities, L. Cummins, A. Sommers, S. BakhtiariRamezani, S. Mittal, J. Jabour, M. Seale, S. Rahimi.
- [6] G. A. Susto, A. Schirru, S. Pampuri, S. McLoone and A. Beghi, "Machine Learning for Predictive Maintenance: A Multiple Classifier Approach," *IEEE Trans. Ind. Informatics*, available as preprint/PDF.
- [7] A. K. S. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," *Mech. Syst. Signal Process.*, 2006.
- [8] S. Susto, A. Schirru et al., "(survey) A systematic literature review of machine learning methods applied to predictive maintenance," *Computers & Industrial Engineering*, 2019.
- [9] K. He, et al., "Review—Deep Learning Methods for Sensor Based Predictive Maintenance," (survey PDF), 2021–2022.
- [10] "Prognostics and Health Management of Industrial Assets: Current Status and Perspectives," *MDPI/PMC review*, 2021.
- [11] "A survey of deep learning-driven architecture for predictive maintenance," *Engineering Applications of Artificial Intelligence*, 2024.
- [12] "Predictive maintenance in Industry 4.0: a survey of planning models and applications," *Sensors / MDPI*.
- [13] "Comparison of deep learning models for predictive maintenance in industrial manufacturing systems," *Scientific Reports*, 2025.
- [14] "Challenges in predictive maintenance – A review," *Journal article*, 2022.
- [15] "A systematic literature review and open research challenges for predictive maintenance in Industry 4.0," 2025.



10.22214/IJRASET



45.98



IMPACT FACTOR:
7.129



IMPACT FACTOR:
7.429



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089  (24*7 Support on Whatsapp)