Volume (1) No (9), 2025
Journal of Global Research in Multidisciplinary Studies (JGRMS)
Review Paper/Research Paper
Available online at https://saanvipublications.com/journals/index.php/jgrms/index

Machine Learning Applications and Techniques for Predictive Maintenance in Industrial Operations: A Review

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Abstract*—The rapid development of Industry 4.0 has transformed industrial systems because it has allowed the use of data-driven solutions to monitor equipment and prevent faults. Predictive maintenance (Pd.M.), which utilizes advanced analytics and uses artificial intelligence to predict when a breakdown is likely to happen, is becoming more and more prevalent in the industry, in addition to more traditional methods like reactive and preventative maintenance. Pd.M. can utilize event logs, control systems, and real-time sensor data streams to enhance equipment availability, minimize downtime, and allocate resources as efficiently as possible. Strong anomaly detectors, defect classifiers, and Remaining Useful Life (RUL) predictions may be obtained using machine learning (ML) and deep learning (DL) models, which are regarded as crucial tools in Pd.M. Across a range of industrial situations, Random Forest (RF) methods, Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) may be applied with great predictive flexibility. Additionally, scalability, efficiency, and sustainability are improved in contemporary operations through integration with digital twins, the Industrial Internet of Things (IIoT), and quantum-enhanced techniques. These developments notwithstanding, there are still challenges, including low data quality, heavy computing requirements, and barriers to adoption by organizations. However, with the further implementation of smart PdM systems, operational efficiency can be enhanced, safety can increase, and sustainable industrial growth can be achieved, marking a crucial step toward smarter and healthier industrial ecosystems.

Keywords*—*Predictive Maintenance, Machine Learning, Deep Learning, Industrial IoT, Digital Twin, Industry 4.0.

I. Introduction

The emergence of Industry 4.0 or the Fourth Industrial Revolution has revolutionized the behaviour of industry by being connected, with huge data sets, smart devices, tailoring, and automatically controlled production processes [1]. Under this new paradigm, maintenance strategies now extend beyond traditional Run-to-Failure (R2F) and Preventive Maintenance (PvM) models to more current Predictive Maintenance (PdM) models. The least complex is R2F, or corrective maintenance, which is done exclusively after the equipment malfunctions, resulting in an expensive cost of downtime. PvM, on the other hand, implements interventions with pre-determined intervals to stop the breakdown, but often causes unnecessary repairs and heightened costs [2]. PdM mitigates these constraints through ongoing monitoring of equipment status and the use of statistical inference, domain knowledge, and ML methods to detect patterns of degradation, thereby identifying the optimal time for a maintenance operation. Through upstream planning of failures, PdM saves time through advance planning, facilitates cost-reduction in operations and encourages the sustainability of production activities [3].

The opportunities provided by increasing access to real-time data about industrial processes have facilitated implementing machine learning (ML) and deep learning (DL) into PdM. RF, LR, SVM, and DT are examples of traditional ML techniques. These all utilize manually generated time, frequency, and time–frequency domain characteristics to operate. In contrast, DL models—such as LSTM networks, RNN, and CNN—can automatically identify hierarchical representations in unprocessed sensor data and facilitate end-to-end prediction [4]. Although DL eliminates the need for sophisticated feature engineering, its models can be considered black boxes due to poor interpretability. However, both ML and DL methods have already demonstrated high predictive maintenance potential and have been increasingly adopted into production systems, making them, as such, at the core of the new era of intelligent manufacturing.

The aim of the article is to give a step-by-step overview of ML techniques employed in Predictive industrial system maintenance. The objective is to describe the available methods, address their advantages and disadvantages, and propose research opportunities in future studies to enhance reliability and efficiency in industry.

A. Structure of the Paper

The structure of this paper is as follows: Section II introduces predictive maintenance strategies in Industry 4.0. Section III explains data sources and pre-processing. Section IV discusses ML and DL techniques. Section V presents a detailed literature review. Section VI provides conclusions and future research directions.

II. Fundamentals of Predictive Maintenance

Predictive Maintenance (PdM) has transitioned from conventional methods, which primarily rely on Condition-based maintenance methods include Preventive Maintenance

(PM) and Reactive Maintenance (RM) [5]. PdM seeks to save operating costs, increase equipment availability, prolong its useful life, and improve employee safety by predicting failures and continuously monitoring mechanical assets. PdM utilizes a wide variety of data streams, despite the obstacles of cost and integration. To deliver dependable prediction capabilities and connect maintenance tasks with organizational objectives in Industry 4.0, AI-based PdM utilizes sensors, data preparation, algorithms, communication, decision-making, and human-computer interfaces.

A. Types of Maintenance

Maintenance strategies efficiency. Traditionally, many systems, such as power grids or data centres, relied on manual tracking utilizing spreadsheets or paper and pencil, which frequently led to reactive maintenance procedures. This approach leads to unplanned outages, which could have been prevented or minimized with more proactive strategies [6]. In general, there are three types of maintenance techniques:

- **Reactive Maintenance (RM):** RM stands for "run-to-failure" maintenance management. Equipment repair and maintenance are only carried out when the equipment has malfunctioned or is at risk of failure.
- **Preventive Maintenance (PM):** To reduce the chance of failures, PM, also known as scheduled maintenance, plans routine maintenance tasks for certain pieces of equipment. Even when the equipment is operating normally, maintenance is carried out to prevent unplanned malfunctions and the associated expenses and downtime.
- **Predictive Maintenance (PdM):** Condition-based maintenance, or PdM, aims to create an appropriate trade-off between maintenance frequency and cost by predicting when equipment is likely to break and identifying which maintenance operations should be performed.

B. Predictive Maintenance Purposes

The PdM's main objectives are to save operating expenses, avoid unscheduled downtime, and enhance system dependability and availability [7]. In the following paragraphs, the objectives of predictive maintenance covered in more detail (Figure 1):

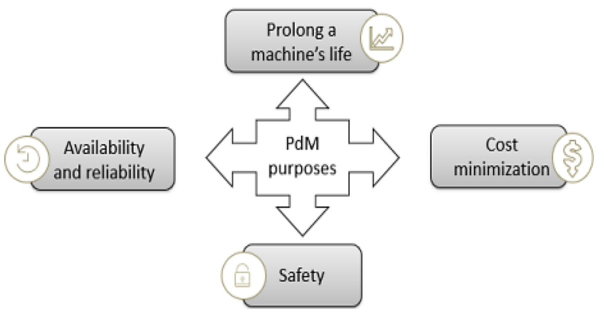

Fig. 1. Purposes of Predictive Maintenance

Here are the PdM purposes are as follows

- **Equipment's Availability and Reliability:** The availability indicates how long a machine is usable and ready for production. Through ongoing data monitoring and several prognostic techniques, a PdM system makes problem diagnosis possible in the future, lowering the frequency of fatal failures and equipment downtime [8]. Minimizing downtime dramatically cuts expenses and enhances productivity. Therefore, since the two objectives are connected, improving the equipment's availability and dependability is essential.
- **Prolong A Machine's Life:** A PdM system seeks to increase a machine's lifespan by enabling ongoing health status monitoring and estimating the machine's remaining usable life. As so, it reduces the possibility of a deadly malfunction. Additionally, a PdM system avoids needless maintenance that might endanger the equipment.
- **Cost Minimization:** The aforementioned goals are connected to the objective of cost minimization. PdM system implementation is costly, but it makes sense from a long-term commercial standpoint. A trustworthy PdM system, for instance, would only permit the storage of the spare parts that are absolutely required, as opposed to holding spare parts that may be required in the future. For this reason, a PdM system maintains a good maintenance procedure while lowering the quantity of spare parts in store and the total storage size.
- **Employee Safety:** A PdM system ensures the safety of workers operating close to or immediately in front of the machinery by keeping an eye on its operational state and preventing catastrophic malfunctions.

C. Data Sources for Predictive Maintenance

The foundation of predictive maintenance (PdM) is the analysis of both historical and current data to forecast asset performance and potential failures. The primary data types include:

- Event data is derived from fault detection through fault isolation, to find the breakdown points, and fault identification, to determine characteristics of the failures and their extent.
- Condition data is commonly recorded from sensors that have identified real-time alerts if critical thresholds are broken, depending on what parameter is being monitored, i.e., temperature and voltage, all from the view of preserving asset performance, prediction, and remediation. The cost of sensors and the difficulties of retrofitting them are compounded by regulatory challenges.
- As alternatives to sensors, it is not uncommon to see streaming data sources such as convenience through satellites, weather stations, and Industrial Control Systems (ICS) PLC and SCADA communication platforms to monitor industrial processes [9]. Furthermore, everything is logged, from warnings to errors and service logs, but their ad-hoc nature presents challenges.
- Finally, the systems mentioned above, such as ERP, CRM, HR, and financial platforms, were not designed for maintenance monitoring. Similarly, spreadsheets were never intended for predictive or preventive maintenance, and while they can be adapted, they are generally inadequate for modern PdM requirements.

D. Key Components in AI-Based Predictive Maintenance

As illustrated in Figure 2, the six main elements of AI-based PdM include user interface and reporting, communication and integration, algorithms, data preparation, and decision-making modules.

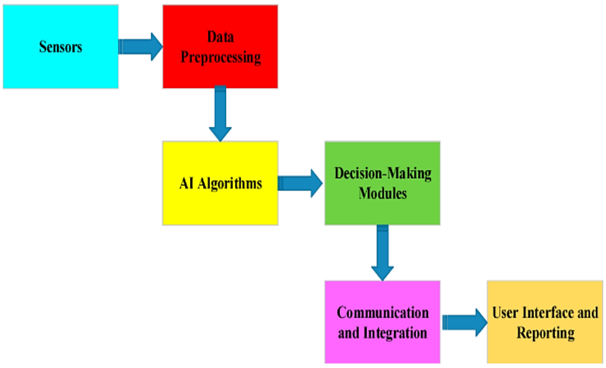

Fig. 2. Key Components of an AI-Based PdM System

This section goes over each element to show how they cooperate to make AI-based PdM possible:

- **Sensors:** Sensors are the main data collectors in a PdM system [10]. To continuously check several parameters, including vibration, pressure, and temperature, these specialized devices are installed on machinery and equipment at key locations. Predictive maintenance analysis is based on real-time sensor data on the equipment's condition.
- **Data Pre-processing:** The raw sensor information is usually noisy and is not uniform. Preparing the data for analysis begins with data preparation. It covers data normalization, data cleaning, and the remediation of missing data. Good quality of data is crucial to proper PdM modelling.
- **AI Algorithms:** The brain of the PdM systems is AI algorithms, including DL and ML techniques. After processing the data, the algorithms identify the most crucial elements pertaining to potential failures. They can also predict anomalies, RUL, and equipment failures by analysing historical data.
- **Decision-Making Modules:** The AI algorithms' predictions and insights are processed by the decision-making modules. These modules are responsible for determining when maintenance is necessary. When necessary, they can initiate notifications to fixers and provide guidance on preventive or corrective fix work and scheduling.
- **Communication and Integration:** Integration and communication aid in making sure that, using the system's results, suitable action is taken. Effective communication with various stakeholders, including management and maintenance personnel, is essential for this element. Additionally, Predictive maintenance integrates enterprise-wide solutions to align with broader business objectives, such as ERP and asset management software.
- **User Interface and Reporting:** In order for maintenance personnel and decision-makers to access these insights, they should be made available through user interfaces and reporting tools. The technologies help users make educated decisions by facilitating the comprehension of complicated data patterns through dashboards, data visualization, and reporting. Dashboards and data visualization are effective tools for communicating predicted data and data insights to decision-makers and maintenance staff. When analyzing complex data trends and making informed decisions, visual representation schemes are helpful.

III. Machine Learning Approaches for Predictive Maintenance

The basics of machine learning (ML) in predictive maintenance (PdM) emphasize its use as a means of processing equipment data to forecast failures, minimize expenditures, and increase reliability. As a subdivision of AI, ML is pattern recognizing and predictive by learning supervised, unsupervised, and reinforcement learning. Classification and defect detection problems can be successfully solved by traditional ML techniques as decision trees, logistic regression, support vector machines, and random forests. DL expands these abilities, where Artificial Neural Networks, CNNs, and RNNs sustain excellent performance for managing complicated, high-dimensional, and time-varying PdM data.

A. Overview of Machine Learning in PdM

According to research, machine learning (ML) is a revolutionary technology in various industries, particularly in the application of predictive maintenance in the oil and gas sector. Predictive maintenance maximizes maintenance schedules and lowers operating costs by using ML to assess equipment data and anticipate issues before they occur. To comprehend how ML is applied in predictive maintenance, one must be familiar with its fundamental ideas and techniques. In essence, ML is a branch of AI that allows systems to learn and get better over time as they get more and more data without explicit programming [11]. The main goal of ML is to develop algorithms that can recognize patterns, decide, and forecast results from incoming data. This factor is especially important in sectors where equipment durability and efficiency are crucial, in the gas and oil industry. The three main categories that include a variety of ML methodologies are supervised learning, unsupervised learning, and reinforcement learning.

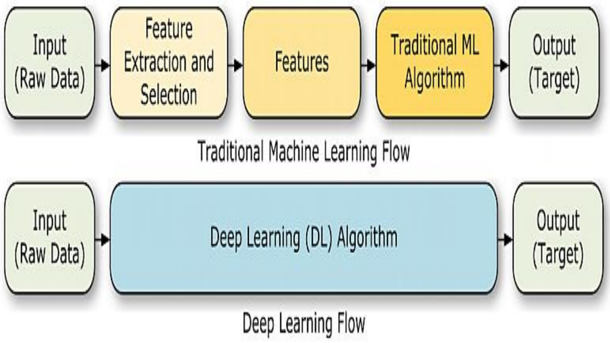

Fig. 3. Flow of Traditional ML and DL Based Methods

The classical ML and DL pipelines, as depicted in Figure 3 [12]. In traditional ML, the explicit processing of the data involves feature extraction and selection prior to the execution of algorithms to produce outputs, whereas in processing raw input data via layered models in DL, relevant features are automatically learned in producing relevant target outputs without human intervention.

B. Machine Learning (ML) Techniques for PdM

The core technology of artificial intelligence (AI) is machine learning (ML), and the advancement of intelligent systems depends on its algorithms [13]. The existence of large-scale data has allowed the broad adoption of ML in a variety of areas, and predictive maintenance (PdM) of industrial equipment has been one of them. One of the most promising fields in which data-driven approaches may be applied is PdM, and the use of ML leads to the possibility of predicting failures and optimizing maintenance schedules [14]. Classical algorithms, such as LR, SVM, DT, and RF, have been widely used in PdM because they have been shown to be highly effective algorithms for classification and regression tasks. They are commonly used in favor of their simplicity, interpretability, and efficiency, although other more complicated and high-performance algorithms are being increasingly developed. Thus, while advanced deep learning and hybrid models are gaining traction, simple yet robust ML techniques remain a practical choice in many PdM scenarios, especially where computational efficiency and explain ability are critical.

- **LR Model:** In machine learning, one of the most used classification models with the simplest technique is logistic regression (LR). Since it is supervised learning, the gathered data must be labelled in order to be included in the model. Moreover, the LR model employs a nonlinear function to convert a linear combination of input properties, ensuring that each output falls between 0 and 1, thereby enabling a probabilistic interpretation.
- **SVM Model:** Binary classification challenges are often addressed by the Support Vector Machine (SVM) model. SVMs have been frequently used in PdM of industrial equipment to determine a specific state based on the signals collected. Furthermore, the SVM model can be applied to multiclass problems, as the provided feature types are varied, and low-dimensional features can be mapped onto hyperplanes.
- **DT and RF Model:** In several fields, including character identification, medical diagnosis, and speech recognition, the application of decision tree (DT) classifiers has proven highly effective. Most importantly, a DT model can repeatedly break down covariate space into subspaces to provide a probable and understandable solution. Consequently, a complicated decision-making process might be seen as a series of challenging decisions. Moreover, the Random Forest (RF) approach is a DT classifier in an ensemble learning collection, and each tree determines the program's overall classification.

C. *Deep Learning (DL)Techniques for PdM*

In this section, the author provides an introduction to DL and highlights the most popular architectures in the context of predictive maintenance (PdM). After the past years, DL models have demonstrated better performance than the conventional methods of statistical and machine learning when plentiful historical data are accessible [15]. DL is a type of ANN inspired by how the human brain functions, extending beyond shallow networks with only one or two hidden layers to deeper architectures capable of capturing complex patterns in data.

- ANNs are composed of neurons that create outputs using non-linear activation functions like rectified linear units (ReLU) and sigmoid, or tanh, and perform linear regressions on inputs using weights. To translate input data into output data, the network's parameters are typically initialised randomly and then modified based on the training dataset. Combining the gradient descent approach with the backpropagation algorithm facilitates this learning process. These allow for the calculation of each neuron's modifications in relation to the network's error output, which is determined using the user-defined cost function.
- Convolutional neural network (CNN) uses convolutional filters to preserve the neighbourhood of neurons in this kind of feedforward network [16]. Drawing inspiration from the visual brain of animals, it finds use in a variety of fields, including signal and image identification, recommendation systems, and NLP. To provide non-linear output, an activation function is applied after the convolutional layer, which is typically linear.
- Recurrent neural network (RNN) models Temporal information by keeping track of the state derived from the network's previous inputs. An adaption of conventional backpropagation for temporal data, the back-propagation over time technique spreads the network's mistake to earlier time occurrences.

D. *Industrial Applications*

Here are the industrial applications are as follows:

1) *Manufacturing and Assembly Lines*

In modern manufacturing environments, predictive maintenance is applied to monitor machines such as motors, bearings, conveyors, and robotic arms. By analyzing vibration, acoustic, and thermal data, ML models can detect early signs of wear, reduce unexpected breakdowns and ensure smooth production. PdM in assembly lines helps minimize downtime, improve product quality, and optimize scheduling of repairs.

2) *Oil & Gas Pipelines and Drilling Rigs*

The oil and gas industry is particularly vulnerable to equipment failures, which can lead to costly downtime, environmental damage, or safety hazards. Predictive models are used to detect leaks, corrosion, or abnormal pressure in pipelines, as well as mechanical failures in drilling rigs. In this vital sector, data-driven PdM reduces maintenance costs, improves safety, and permits proactive interventions.

3) *Power Plants and Energy Systems*

In energy generation, whether it is traditional power plants, wind turbines, or solar arrays, PdM is crucial in maintaining a stable power supply. Predictive models can identify cracks in turbine blades, generator faults, and transformer degradation before disastrous failures occur. These applications can be used to improve the reliability of assets, provide longer equipment life lows as well as help in producing sustainable energy.

4) *Aerospace and Transportation*

The transportation and aerospace industries require great safety and dependability. PdM is used extensively on aircraft engines, avionics systems and railway parts like rail wheels and rail brakes. The frequent surveillance and ML-assisted fault prediction optimize flight delays and enhance the safety of passengers and optimization of maintenance schedules, where it is imperative to abide by stringent safety rules.

5) *Smart Factories (Industry 4.0 Context)*

Safety and reliability are required in the aerospace and transportation industries. PdM is extensively limited to the engine of aircraft, avionics, and railway equipment, like wheels and brakes. Constant monitoring and predicting of faults using ML decreases the time loss in flights, increases patient safety and optimizes by maintaining schedules and facilities, which is in line with the high standards of safety.

IV. Evaluation Metrics and Challenges in Predictive Maintenance

The metrics and challenges of predictive maintenance (PdM) evaluation are crucial for presenting objective evidence of the model's practicality and relevance in the actual world. Among the evaluation measures used in classification are F1-score, recall, accuracy, and precision. In the case of maintenance systems, consider measures such as MTBF, MTTR, MTTF, OEE, and failure rate. The metrics used to measure the dependability of the system performance [17]. Although PdM use can have many benefits, obstacles to its implementation exist. Principles and organizational expenses are significant, and skilled human operators are usually required to carry out repairs due to human error. There can be great restrictions on data in the initial stages of adoption or implementation. Such obstacles should be overcome to make the most of the Industry 4.0 maintenance strategies.

A. *Common Evaluation Metrics*

The most frequent measurement combinations that are frequently used to identify the performance of predictive maintenance models are as follows:

Accuracy: One of the most popular assessment metrics used to determine the performance of classification algorithms is accuracy. The expression for classification accuracy is found in Equation (1):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Precision: A classifier is an absolute measure of how correct classification is once a prediction stage has been made. True positives (TP) divided by the total of TP and FP is the assessment metric, as shown in Equation (2) below:

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

Sensitivity: Recall, or sensitivity, is a parameter of how a classifier goes about identifying positive instances. As seen in Equation (3) below, it determines the proportion of successfully recognized positive cases by dividing TP by the sum of TP and FN:

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

F1-Score: The F1-score, a statistic used in classification approaches to describe a model's overall performance, is the harmonic mean of accuracy and recall [18]. The measure is a number between 0 and 1, with a high number denoting excellent classification performance and a low number denoting subpar classification performance. Equation (4) provides the F-score:

$$F1 - Score = \frac{2*Precision*Recall}{(Precision+Recall)} \tag{4}$$

These assessment indicators present a balance between the accuracy, topicality and thoroughness of predictions in the evaluation models of predictive maintenance. The combination of them makes sure the classification performance is well measured under various scenarios of faults.

B. *Mean Time Between Failures (MTBF) and Maintenance-Specific Metrics*

Mean Time between Failures (MTBF) and other metrics related to maintenance are necessary to measure the strength of a system as well as the efficiency demonstrated by its maintenance. These measures are used to estimate life of the equipment and the optimization of maintenance.

1) *Mean Time Between Failures (MTBF)*

MTBF is often regarded as one of the most significant reliability parameters in predictive maintenance. It is an equivalent of the average working life of a system or part between two failures and is expressed as in Equation (5):

$$\text{MTBF} = \frac{\text{Total Operational Time}}{\text{Number of Failures}} \tag{5}$$

The increasing MTBF value denotes longer periods of equipment operation without unexpected shutdowns. In predictive maintenance, the main target is to prolong MTBF. The longer this value is, the better monitoring systems perform, and the more effectively the machine learning model predicts failures before they occur [19]. TBF is especially suited for comparing systems' maintenance strategies and tracing the reliability of a system as it ages.

2) *Maintenance-Specific Metrics*

In addition to the MTBF, there are several other maintenance metrics that are commonly employed by maintenance professionals to define system performance and reliability:

- **Mean Time to Repair (MTTR):** Average time required to restart machinery following a malfunction.
- **Mean Time To failure (MTTF):** Average time equipment operates until the first failure, non-repairable systems.
- **Overall Equipment Effectiveness (OEE):** A combined measure that takes into account product quality, performance efficacy, and availability.
- **Failure Rate (λ):** The number of failures recorded per time period. Commonly used in reliability engineering.
- **Availability Ratio:** The amount of time in which a piece of equipment is operational compared to the entire observation period.

C. *Key Challenges of Predictive Maintenance*

It seems certain that Industries have embraced predictive maintenance, but obstacles stand in the way of its general application as a prudent maintenance method [20]. Even though predictive maintenance algorithms are now available, businesses hoping to take advantage of Industry 4.0 still have to weigh the upfront expenses of purchasing the necessary tools, software, and expertise against the possibilities of predictive maintenance [21]. When predictive maintenance is just getting started and there is little to no real information on typical and unusual equipment performance, this drawback is most noticeable. This is particularly true when designing new systems, as there is no prior knowledge of how they operate.

1) *Financial and Organizational Limits*

The expenses of each new investment must be carefully considered by for-profit businesses. Installing sensors, gathering data, creating and maintaining models, and performing maintenance tasks are all costs associated with implementing predictive maintenance (PdM). The kind and complexity of the equipment, the sophistication of the sensors, consultation and installation fees, and whether the necessary knowledge is available internally or needs to be acquired externally are just a few of the variables that can significantly affect these expenses.

2) Machine Repair Activity Constraints

Estimating a component's remaining useful life (RUL) enables more effective maintenance scheduling; however, the actual repair process remains constrained by human involvement and the absence of autonomous self-maintenance. Since the majority of machine components still require manual supervision and intervention, the skill level and managerial calibre of human operators have a significant impact on how well maintenance works. Industrial machines, in particular, function reactively by executing predefined commands and do not have the capacity to independently question or adapt maintenance plans.

3) Data Source Limits

To create a production process management model, pertinent data must be available. But when businesses first introduce production process management, they almost never have all the necessary information. The holes must be identified and filled using the available data.

V. Literature Review

In this section, a literature review of predictive maintenance in industrial systems has been provided with emphasis on ML and DL methods, integration of IIoT, quantum-enhanced systems, anomaly detection, Remaining Useful Life (RUL) prediction, and digital twin design as the means of enhancing accuracy, scalability, and sustainable industrial operations.

Pandey et al. (2025) discuss a predictive methodology that utilizes real-time data from motor-mounted temperature, vibration, and current sensors. Advanced algorithms analyze the data to identify unusual patterns and predict when equipment may fail, allowing for preventive repairs before any issues arise. The ML algorithms in predictive maintenance systems are typically used to predict equipment failures. At least in terms of comparing the algorithms, the highest quality of the prediction of motor failures can be seen in the method known as Random Forest (RF). By facilitating more effective scheduling and informed decision-making, Predictive maintenance using data can drastically reduce maintenance costs and downtime. Industrial motor maintenance may be enhanced by integrating MQTT messaging, ML, and technology for the IIoT. This is consistent with Industry 4.0's goals for environmentally friendly [22].

Chouhan et al. (2025) discuss the integration of quantum algorithms on Google Quantum AI for optimising IIoT-based predictive maintenance systems. Faster data processing is made possible by methods such as quantum k-means clustering and quantum support vector machines (QSVM), which further enhance the accuracy of the anomaly detection process. Techniques such as the Quantum Approximate Optimization Algorithm (QAOA) help optimize schedules for maintenance and resource allocation, thereby reducing downtime and operational costs. Therefore, quantum simulations do better forecasts with the proper handling of equipment wear and material degradation, which enables proactive maintenance actions. Sustainably implemented quantum-fortified techniques are expected to yield the fewest false positives, minimize unplanned downtime events, and optimize maintenance resource usage [23].

Juliet's (2025) strategy plans maintenance to reduce downtime and maximise operational effectiveness. The fact that inaccurate forecasts and false alarms might result from low-quality data, it challenging to obtain reliable, consistent, and well-integrated IoT sensor data. Scaling real-time fault detection and prediction requires substantial computational power and optimized algorithms to process the continuous influx of data from multiple machines. To address data quality and integration issues while enhancing real-time processing and scalability, a Custom Neural Network technique can be used to improve IoT sensor data accuracy and consistency, and efficiently manage the computational demands of continuous data influx for fault detection and prediction. The proposed system, leveraging an extended Neural Network technique, enhances prediction accuracy by efficiently managing diverse industrial datasets and improves real-time fault detection through optimized data processing and reduced latency [24].

Razzaq, Jazzel Mehmood and Khan (2024) intend to compare basic regression and ARIMA models to investigate RNNs' potential for predictive maintenance in a use case involving industrial machinery. It also highlights the significant improvement RNNs make over the aforementioned strategies. This research also proposes an extension of the existing virtual reality-based digital twin architecture to incorporate automated predictive maintenance of the machine. Moreover, the proposed digital twin architecture serves as a foundation for the automated predictive maintenance of any product. Smart manufacturing in Industry 4.0 has come about due to digital twin technology [25].

Narayanan et al. (2024) analyze predictive maintenance using ML across a number of industries. It describes the methodology for gathering and pre-processing information from various sensors and equipment logs, as well as the important process of feature engineering to isolate meaningful aspects of the information. All relevant approaches to ML algorithms and the methods for training the model are discussed in detail. Additionally, the study highlights the crucial role of anomaly detection strategies in the early identification of failures, enabling timely preventive intervention in the event of machinery failures. The main focus of this effort is on developing predictive maintenance models that calculate the equipment's remaining useful life (RUL). RUL projections are discussed when determining the thresholds of the maintenance operations, and they are aimed at balancing performance and costs [26].

Jadhav et al. (2023) investigate industrial machinery predictive maintenance. Using a Google form, collected several opinions from specialists in the fields of ML, IoT, and Information Technology. Learned from this survey that if don't take any proactive steps to maintain industrial equipment, a lot of rubbish is produced, which further contributes to pollution and several other issues, including a lack of equipment and many others. IoT is extensively utilised, and gadgets are common in many different businesses. Industrial IoT uses sensors and IoT devices to keep an eye on surrounds and equipment, ensuring the optimal functioning of equipment and processes. Predictive maintenance, which monitors equipment health to forecast component breakdown, is one industrial IoT solution that has lately attracted attention. Effective Predictive Maintenance is made possible by using ML algorithms to gather, analyse, and interpret vast volumes of data [27].

Table I presents a summary of the literature review, highlighting the focus, approach, key findings, challenges, and proposed future directions of each study.

TABLE I. COMPARATIVE ANALYSIS OF LITERATURE REVIEW ON MACHINE LEARNING FOR PREDICTIVE MAINTENANCE IN INDUSTRIAL SYSTEMS

Reference	Study On	Approach	Key Findings	Challenges	Future Direction
Pandey et al. (2025)	Predictive maintenance using vibration, current, and temperature sensors on motors	Machine Learning with Random Forest algorithm for anomaly detection	RF shows highest accuracy in predicting motor failures	Ensuring real-time accuracy and handling diverse data streams	Enhance integration with IIoT and optimize decision-making
Chouhan et al. (2025)	Quantum algorithms for IIoT-based predictive maintenance	Quantum SVM, Quantum K-means, and QAOA for optimization	Quantum methods improve speed, scalability, and reduce false positives	Quantum algorithms require advanced infrastructure and integration	Expand use of quantum ML in industrial predictive maintenance
Juliet (2025)	Custom Neural Network for IoT sensor data quality and real-time fault detection	Extended Neural Network for improved data accuracy and processing	Improved IoT data consistency and reduced latency in real-time fault detection	Scalability and computational load for continuous IoT data streams	Enhance IoT fault detection scalability with optimized NN
Razzaq, Jazzel Mehmood and Khan (2024)	RNNs for predictive maintenance and integration with digital twin	Comparative analysis of RNNs, Regression, and ARIMA with VR-based digital twin	RNNs outperform regression and ARIMA, VR digital twin enhances predictive maintenance	Complexity in integrating VR digital twin with predictive maintenance	Further enhance VR digital twins for general industrial use
Narayanan et al. (2024)	ML-based predictive maintenance with focus on RUL estimation	Data preprocessing, feature engineering, anomaly detection, RUL projection	RUL-based predictions balance cost-effectiveness and reliability	Defining reliable thresholds for RUL-based decisions	Refine RUL models and improve anomaly detection accuracy
Jadhav et al. (2023)	Survey of expert opinions on IoT and predictive maintenance	Google form survey on IoT, ML, and IT experts	Predictive maintenance reduces waste and pollution, IoT widely adopted	Need for proactive adoption and addressing environmental concerns	Promote sustainable practices and expand IoT-based predictive maintenance

VI. CONCLUSION AND FUTURE WORK

Reactive and preventative maintenance methods have given way to predictive maintenance (PdM) as a result of Industry 4.0. Utilizing real-time sensor data, including vibration, temperature, and current, PdM lowers operating costs, increases equipment availability, and minimizes downtime. In defect detection, anomaly identification, and ML and DL models like RF, SVM, CNN, and RNN have demonstrated exceptional performance in estimating Remaining Useful Life (RUL). Beyond traditional methods, integration with Industrial IoT platforms, digital twins, and emerging quantum-based algorithms provides enhanced scalability, faster computation, and improved sustainability in industrial systems. These developments enhance safety, dependability, and resource efficiency, while also facilitating optimal decision-making. However, issues such as uneven data quality, high processing demands, and implementation expenses —whether monetary or organizational —continue to be major obstacles. Future research should concentrate on creating energy-efficient prediction models, scalable, and interpretable. Advancements in quantum ML, digital twin integration, and sustainable IoT frameworks can enhance reliability. However, addressing data gaps, standardization, and cybersecurity remains critical for robust real-time industrial adoption. Moreover, greater emphasis on transfer learning and federated learning can enable knowledge sharing across industries. Collaborative human–AI systems will further ensure trust, adaptability, and widespread use of solutions for predictive maintenance.

REFERENCES

[1] T. Zonta, C. A. da Costa, R. da R. Righi, M. J. de Lima, E. S. da Trindade, and G. Li, “Predictive maintenance in the Industry 4.0: A systematic literature review,” *Comput. Ind. Eng.*, vol. 150, no. October, p. 106889, Dec. 2020, doi: 10.1016/j.cie.2020.106889.

[2] T. P. Carvalho, F. A. A. M. N. Soares, R. Vita, R. da P. Francisco, J. P. Basto, and S. G. S. Alcalá, “A systematic literature review of machine learning methods applied to predictive maintenance,” *Comput. Ind. Eng.*, vol. 137, Nov. 2019, doi: 10.1016/j.cie.2019.106024.

[3] S. Ayvaz and K. Alpay, “Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time,” *Expert Syst. Appl.*, vol. 173, no. January, p. 114598, 2021, doi: 10.1016/j.eswa.2021.114598.

[4] A. Hakami, “Strategies for overcoming data scarcity, imbalance, and feature selection challenges in machine learning models for predictive maintenance,” *Sci. Rep.*, vol. 14, no. 1, pp. 1–14, 2024, doi: 10.1038/s41598-024-59958-9.

[5] R. Patel and P. Patel, “A Survey on AI-Driven Autonomous Robots for Smart Manufacturing and Industrial Automation,” *Tech. Int. J. Eng. Res.*, vol. 9, no. 2, pp. 46–55, 2022, doi: 10.56975/tijer.v9i2.158819.

[6] T. Zhu, Y. Ran, X. Zhou, and Y. Wen, “A Survey of Predictive Maintenance: Systems, Purposes and Approaches,” 2025.

[7] O. Manchadi, F. E. Ben-Bouazza, and B. Jioudi, “Predictive Maintenance in Healthcare System: A Survey,” *IEEE Access*, vol. 11, no. May, pp. 61313–61330, 2023, doi: 10.1109/ACCESS.2023.3287490.

[8] C. Mokkapati and S. Jain, “Enhancing Site Reliability Engineering (SRE) Practices In Large-Scale Retail Enterprises,” vol. 9, no. 11, pp. 870–886, 2021.

[9] V. M. Z. Wickern, “Challenges and Reliability of Predictive Maintenance,” *Rhein-Waal Univ. Appl. Sci.*, vol. nan, no. March, p. 16, 2019, doi: 10.13140/RG.2.2.35379.89129.

[10] A. Ucar, M. Karakose, and N. Kırımça, “Artificial Intelligence for Predictive Maintenance Applications: Key Components, Trustworthiness, and Future Trends,” *Appl. Sci.*, vol. 14, no. 2, 2024, doi: 10.3390/app14020898.

[11] E. O. Nwulu, T. Elete, O. V. Erhueh, and O. A. Akano, “Machine learning applications in predictive maintenance: Enhancing efficiency across the oil and gas industry,” *Int. J. Eng. Res. Updat.*, vol. 5, no. 1, pp. 013–027, Sep. 2023, doi: 10.53430/ijeru.2023.5.1.0017.

[12] M. Drakaki, Y. L. Karnavas, I. A. Tziafettas, V. Linardos, and P.

Tzionas, "Machine Learning and Deep Learning Based Methods Toward Industry 4.0 Predictive Maintenance in Induction Motors: A State of the Art Survey," *J. Ind. Eng. Manag.*, vol. 15, no. 1, pp. 31–57, 2022, doi: 10.3926/jiem.3597.

[13] R. Patel and P. Patel, "Machine Learning-Driven Predictive Maintenance for Early Fault Prediction and Detection in Smart Manufacturing Systems," *ESP J. Eng. Technol. Adv.*, vol. 4, no. 1, 2024, doi: 10.56472/25832646/JETA-V4I1P120.

[14] W. Zhang, D. Yang, and H. Wang, "Data-Driven Methods for Predictive Maintenance of Industrial Equipment: A Survey," *IEEE Syst. J.*, vol. 13, no. 3, pp. 2213–2227, 2019, doi: 10.1109/JSYST.2019.2905565.

[15] O. Serradilla, E. Zugasti, J. Rodriguez, and U. Zurutuza, "Deep learning models for predictive maintenance: a survey, comparison, challenges and prospects," *Appl. Intell.*, vol. 52, no. 10, pp. 10934–10964, 2022, doi: 10.1007/s10489-021-03004-y.

[16] S. Mathur and S. Gupta, "Classification and Detection of Automated Facial Mask to COVID-19 based on Deep CNN Model," in *2023 IEEE 7th Conference on Information and Communication Technology, CICT 2023*, 2023. doi: 10.1109/CICT59886.2023.10455699.

[17] K. M. R. Seetharaman, "Analysing the Role of Inventory and Warehouse Management in Supply Chain Agility: Insights from Retail and Manufacturing Industries," *Int. J. Curr. Eng. Technol.*, vol. 12, no. 06, pp. 583–590, Jun. 2022, doi: 10.14741/ijcet/v.12.6.13.

[18] A. Buabeng, A. Simons, N. K. Frempong, and Y. Y. Ziggah, "Predictive Maintenance Model Based on Multisensor Data Fusion of Hybrid Fuzzy Rough Set Theory Feature Selection and Stacked Ensemble for Fault Classification," *Math. Probl. Eng.*, vol. 2022, no. 1, pp. 1–24, Jun. 2022, doi: 10.1155/2022/4372567.

[19] T. Ortalli, A. Di Martino, M. Longo, and D. Zaninelli, "Make-or-Buy Policy Decision in Maintenance Planning for Mobility: A Multi-Criteria Approach," *Logistics*, vol. 8, no. 2, 2024, doi: 10.3390/logistics8020055.

[20] R. Patel and P. B. Patel, "The Role of Simulation & Engineering Software in Optimizing Mechanical System Performance," *TIJER – Int. Res. J.*, vol. 11, no. 6, pp. 991–996, 2024.

[21] M. Achouch *et al.*, "On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges," *Appl. Sci.*, vol. 12, no. 16, 2022, doi: 10.3390/app12168081.

[22] S. Pandey, D. Srivastava, R. Maurya, and M. S. Khan, "Predictive Maintenance for Industrial Equipment (Motor) Using IoT," in *2025 3rd International Conference on Communication, Security, and Artificial Intelligence (ICCSAI)*, 2025, pp. 917–921. doi: 10.1109/ICCSAI64074.2025.11064125.

[23] S. Chouhan, R. Sandhu, S. Kumar, and S. M. N. Islam Naz, "Optimizing Industrial IoT Predictive Maintenance Using Quantum Algorithms on Google Quantum AI," in *2025 International Conference on Emerging Smart Computing and Informatics (ESCI)*, 2025, pp. 1–5. doi: 10.1109/ESCI63694.2025.10988369.

[24] A. H. Juliet, "AI-Driven Predictive Maintenance for Industrial IoT with Real-Time Fault Detection and Prediction," in *2025 8th International Conference on Electronics, Materials Engineering & Nano-Technology (IEMENTech)*, 2025, pp. 1–6. doi: 10.1109/IEMENTech65115.2025.10959502.

[25] H. A. Razzaq, M. Jazzel Mehmood, and F. Khan, "Leveraging Recurrent Neural Networks in Virtual Reality-based Digital Twin Models for Enhanced Predictive Maintenance of Industrial Machines," in *2024 26th International Multi-Topic Conference (INMIC)*, 2024, pp. 1–6. doi: 10.1109/INMIC64792.2024.11004403.

[26] L. K. Narayanan, L. S, H. R, D. Jayalakshmi, and V. R. Vimal, "Machine Learning-Based Predictive Maintenance for Industrial Equipment Optimization," in *2024 International Conference on Trends in Quantum Computing and Emerging Business Technologies*, 2024, pp. 1–5. doi: 10.1109/TQCEBT59414.2024.10545280.

[27] A. Jadhav, R. Gaikwad, T. Patekar, S. Dighe, B. Shaikh, and N. S. Patankar, "Predictive Maintenance of Industrial Equipment Using IoT and Machine Learning," in *2023 4th International Conference on Computation, Automation and Knowledge Management (ICCAKM)*, 2023, pp. 1–5. doi: 10.1109/ICCAKM58659.2023.10449546.

