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THE ROLE OF MACHINE LEARNING(ML)-DRIVEN-DIGITAL TWINS FOR SMART MANUFACTURING PREDICTIVE MAINTENANCE: A REVIEW

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Abstract: Predictive maintenance is one of the approaches that can allow making the industry more sustainable, safe, and profitable. Considering the implementation of machine learning (ML), digital twin (DT) and the Industrial Internet of Things (IIoT), this paper is going to reflect on the advances of predictive maintenance (PdM) in a connected manufacturing. Aspects of PdM such as data gathering, sensor connections, and forecasting modelling are discussed, albeit with more focus on condition-based maintenance, forecasting anomalies, and real-time fault detection. The paper discusses various ML mechanisms supervised, unsupervised and reinforcement learning, and the contributions they make to the monitoring of equipment health and decisions. The applicability regarding dynamic digital twin applications is discussed to simulate, predict and optimise the expected system performance without interference with the current process in the system. A comprehensive literature review presents cutting-edge PdM frameworks, including cloud–edge hybrid architectures, multi-agent systems, adaptive AI models. Challenges such as implementation complexity, scalability, and data quality limitations are discussed alongside solutions aimed at interoperability, lightweight modeling, and cross-domain adaptability. According to the results, PdM is an essential component of the industry 4.0 revolution since it can drastically cut down on downtime, increase the lifespan of equipment, and improve operational efficiency through the use of AI, DT, and the Internet of Things.

Keywords: Predictive Maintenance, Smart Manufacturing, Digital Twin, Machine Learning, Industrial IoT.

1 INTRODUCTION

Manufacturing companies today are trying to become more competitive by using new technologies, also known as "enabling technologies," to help the industry grow. The world's economy can be strategically advanced through focussing on three levers: innovation, sustainability, and competitiveness [1]. Regarding this, academics and business leaders are focussing on how digital manufacturing systems encourage "sustainability" and a "circular economy" inside existing enterprises. In reality, multiple writers have acknowledged that sustainability and innovation are two of the most important concerns for smart manufacturing systems going forward [2].

A "digital twin" is an identical digital representation of an item, service, or procedure that shares all the features and advantages listed above. The term "Digital Twin" (DT) was coined by Grieves and Vickers to represent "a collection of virtual information constructs that completely describes a potential or actual physical manufactured product from the microtomic level to the macro geometrical level [3]." In a perfect world, we could physically examine a product's digital counterpart and discover all about it. Modern methods including as optimisation, real-time monitoring, simulation, twinning, and analytics are utilised by DT to accomplish this objective. Many people think that digital twins are the next big thing in simulation and the inevitable next step for digital technology [4]. "Smart manufacturing," an idea with American origins that is finding increasing use globally, has recently been gaining traction in academia and business. It seems like a lot of manufacturing systems are trying to pass themselves off as SM systems (SMSs). SM refers to a collection of methods in manufacturing that guide operations via the use of information and communication technologies (ICTs) and networked data [5][6][7]. Production planning and control are ICT-related topics. Raw materials are transformed into final things by a process or series of processes. This was the traditional approach to manufacturing.

Predictive maintenance (PDM) is highly relevant here since it uses this state-of-the-art technology to anticipate equipment breakdowns, which in turn reduces maintenance costs and downtime [8][9]. When compared to PDM, reactive and preventative maintenance methods fail. Reactive maintenance focusses on restoring broken equipment, while preventative maintenance plans maintenance regardless of the existing condition of the equipment [10]. Problems can be quickly identified using PDM since it analyses data from several sensors in real-time. The actual functioning of the equipment can also be used to organize repair chores. This enhances operational efficiency and also increases the lifespan of machines. Many new technologies are bringing more data available and making the concept of smart buildings more popular [11][12]. Digital twins, smart meters, the IoT, cyber-physical systems (CPS), BIM, AI, ML, and AI are all part of this category. Here, building managers should focus on reducing energy use by making use of the new smart features that provide quicker communication and data sharing.

Machine learning (ML) is a foundational technology that can make manufacturing smarter and give it the capabilities it needs to be more flexible and adaptable [13][14]. Industry 4.0, the smart industrial era, is replacing the traditional manufacturing period, and these ML developments are bringing it about. With the rise of digital solutions and advanced technologies like the IIoT, cloud computing, advanced robotics, digital twins, additive manufacturing, and augmented/virtual reality, ML is gaining prominence in the manufacturing sector.

1.1 Structure of the paper

The structure of this paper follows as: Section II covers multi-cloud models/types. Section III outlines cost components IN Multi-Cloud Infrastructure. Section IV details cost optimisation strategies. Section V reviews related studies. Section VI gives conclusions and future directions.

2 PREDICTIVE MAINTENANCE COMPONENTS IN SMART MANUFACTURING

Predictive maintenance, or PdM, is the newest way that many businesses do maintenance. The reliability of essential services, such as power plants, public services, transportation networks, and emergency services, must never be compromised [15][16]. Predicted data is usually required for long-term planning of various operational tasks (e.g., production, inventory, maintenance, etc.). There are a few key components, as seen in Figure 1, and maintenance cannot always be conducted everywhere due to logistical and technological limitations [17].

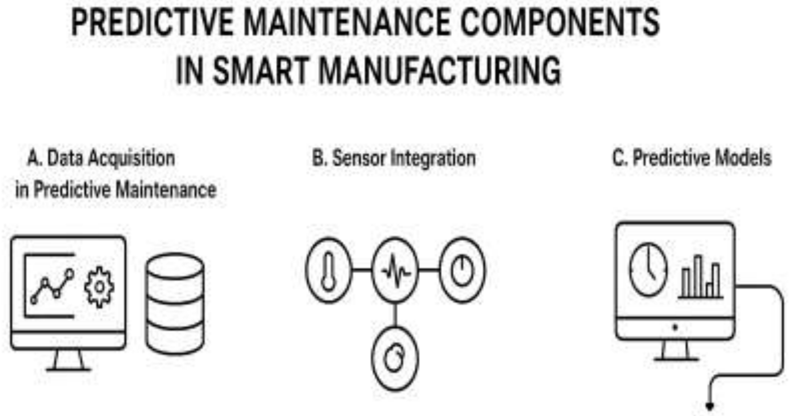

Figure 1: Components of Smart Manufacturing

1.2 Data Acquisition in Predictive Maintenance

Software and many devices make up the data collecting system. Data measurement and transfer between systems is facilitated by these software and hardware components [18][19]. Additionally, the data collecting system shows the sensor system in action. The data acquisition system learns to detect data and the process of transferring it with the aid of a sensor system. In addition, it has been noted that the data collecting program is also involved in carrying out other tasks [20]. The software system responsible for gathering data and storing it in different devices is shown in Figure 2.

Figure 2: Data Acquisition Components

- **Maintenance Records and Logs:** Investigating equipment performance trends and patterns by reviewing maintenance records. With this information, and better understand typical failure modes and train prediction algorithms.
- **Operational Data:** Assembling information about operational factors like load, speed, and usage trends. Understanding how equipment is used can provide insights into potential stress points that may lead to failures.
- **Environmental Data:** Monitoring environmental conditions (e.g., humidity, temperature variations) that may affect equipment performance. This information can be crucial for understanding external factors contributing to wear and tear.

1.3 Sensor Integration

Sensors, actuators, effectors, controllers, and control loops are the primary technologies utilised in the modern production system, however there are others [21]. In order to improve product quality, sensors play an essential role in smart factories by collecting and integrating precise data into the production processes. Figure 3 displays the sensors. To detect the existence of an object or activity, sensors use electrical, opto-electrical, or electronic devices made of sensitive materials.

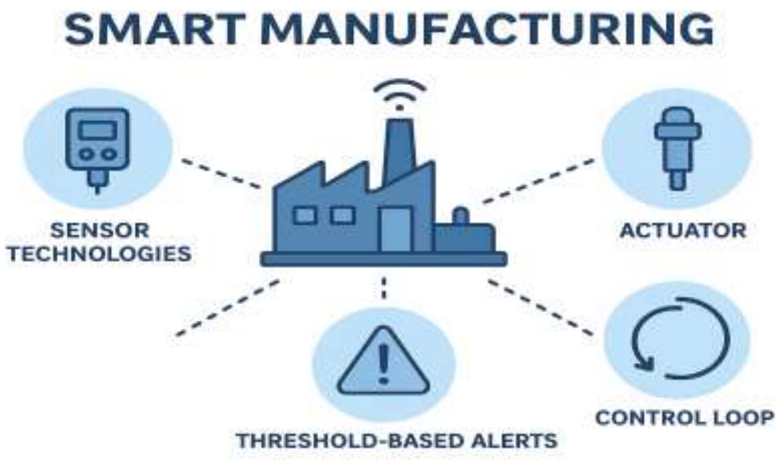

Figure 3: Sensor Integration in Predictive Maintenance

- **Sensor Technologies:** Predictive maintenance relies on continuous data gathering from various sensors that measure things like vibration, temperature, pressure, and more. The sensors in these Internet of Things devices can collect data in real-time by linking to the internet. This data can then be examined to discover patterns [22].
- **Threshold-based alerts:** The ability to set alerts based on predetermined thresholds allows for the triggering of maintenance actions whenever a parameter or piece of equipment surpasses a specific value.

1.4 Predictive Models

A wide variety of smart manufacturing operations can make use of predictive models [23]. There is an almost infinite list of potential variables and control parameters that might need to be anticipated in order to make local decisions, such as client or downstream demands, processing times, tool wear, and the time or duration of necessary maintenance tasks. Figure 4 displays some of the techniques used in predictive models.

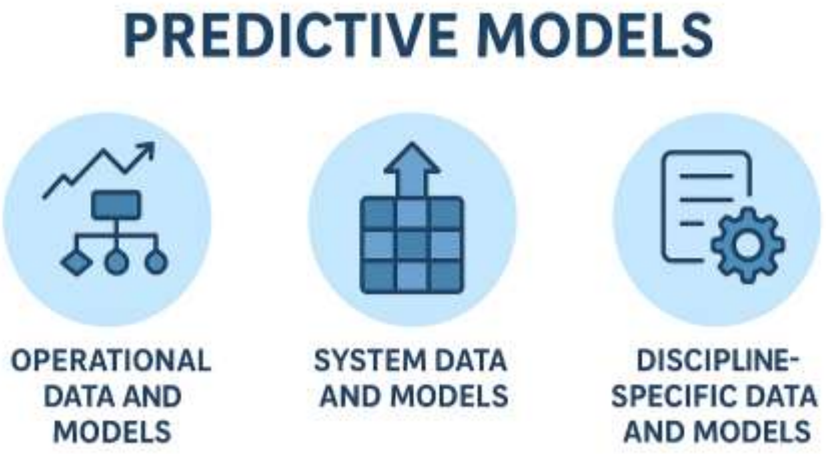

Figure 4: Predictive Models in Smart Manufacturing

- **Operational data and models:** The models that control the interdependencies among the models, record the interdependencies among the models, and define the system's operational use to investigate matters of interest.
- **System data and models:** Models of systems and the data used to support them that cut across many fields of engineering and business.
- **Discipline specific data and models:** Data and models relevant to a specific field.

Table I summarizes the components of the Predictive Maintenance Framework in Smart Manufacturing, outlining each section's purpose, description, key data/technologies, and example outputs. Data Acquisition focuses on collecting and storing operational, maintenance, and environmental information; Sensor Integration emphasizes real-time monitoring using IoT devices and threshold-based alerts; and Predictive Models leverage operational, system-wide, and discipline-specific data to forecast equipment needs and optimize processes are given below.

TABLE I: SUMMARY OF PREDICTIVE MAINTENANCE FRAMEWORK COMPONENTS IN SMART MANUFACTURING

Section	Purpose	Description	Key Data/Tech	Example Outputs
Overview	Introduce PdM in smart manufacturing	Forecast-based maintenance in high-reliability industries to plan operations and reduce downtime	Reliability-critical sectors (power plants, transport, emergency services)	Maintenance schedules, inventory planning
Data Acquisition	Gather and store relevant data	Use of software, devices, and sensors to measure, transfer, and store data	Maintenance logs, operational data, environmental data	Failure mode patterns, stress point detection
Sensor Integration	Real-time monitoring of equipment	Sensors, actuators, effectors, controllers, and loops to improve product quality	Temperature, pressure, vibration sensors; IoT devices	Alerts when thresholds exceeded, continuous health data
Predictive Models	Forecast performance and needs	Models to predict demand, material arrival, processing time, tool wear, maintenance duration	Operational, system-wide, and discipline-specific models	Demand forecasts, maintenance timing, process optimization

3 MACHINE LEARNING (ML) APPROACHES FOR PREDICTIVE MAINTENANCE

ML methods are among the most popular ways to diagnose problems, make predictions, and spot abnormalities. The term "data-driven approaches" describes methods that anticipate RUL without knowing the underlying physical structure or degradation, but instead rely on a variety of data sources, such as sensor measurements [24]. Machine learning techniques improve the accuracy of equipment state predictions by learning from past data and continuously adjusting to new data. Such approaches can increase the quality of predictions by processing vast volumes of data and taking various aspects into consideration [25]. Aside from offering decision-making management to improve system performance, new machine learning (ML) technologies demonstrate enormous promise for data analysis. Applying machine learning techniques in various domains, such as manufacturing, follows a specific pattern.

1.1 Supervised Learning (SL)

The process of supervised learning entails constructing a model using input and output data. Because of this, the computer can understand the relationship between them, which allows it to make predictions based on data that has never been observed before [26]. It is commonly used for jobs that involve predicting categories (classification tasks) and estimating continuous values (regression jobs). Next, evaluate the model's performance using metrics like accuracy or error rates, which vary with the type of task at hand.

- **Models:** DL models that use SVMs, RFs, and GBMs necessitate labelled datasets that depict normal and defective states over time. These models learn from past equipment failures to classify future operational conditions. While effective for well documented machinery failures, supervised learning requires large, high-quality datasets, which may not always be available in industrial settings.

1.2 Unsupervised Learning (UL)

Unsupervised ML methods facilitate the extraction of analytical insights from unlabelled data, which in turn facilitates the analysis of raw datasets [27]. Unsupervised learning has come a long way in the last few years, thanks to breakthroughs in areas such as factor analysis, latent models, hierarchical learning, clustering techniques, and outlier detection. A major step forward for ML has been the rise of "deep learning" and other unsupervised learning techniques, which make it possible to examine raw data with less domain expertise and engineering required to create features.

- **Models:** Anomalies can be detected by these models even in the absence of labelled failure data. Early defect identification in systems with little failure history can be achieved using techniques like K-means clustering, Isolation Forests, and Autoencoders, which detect departures from regular operational patterns. Unsupervised models continuously learn from incoming sensor data, enabling adaptation to new failure modes that may not have been previously recorded.

1.3 Reinforment Learning (RL)

A third machine learning (ML) approach that emphasises experience-based learning is reinforcement learning, which combines supervised and unsupervised learning methods in a hybrid fashion using training data that falls somewhere in the middle [28]. One way reinforcement learning differs from the others is that it aims to train robots to perform the right things. Machines can learn from their environments by receiving positive reinforcement (feedback) when they respond appropriately to their present condition, and negative reinforcement (feedback) when they respond badly. Common reinforcement learning tasks include control and planning.

- **RL Use Case:** Reinforcement learning can further enhance predictive maintenance outcomes. By integrating anomaly detection with historical failure classification and adaptive decision-making, industries can achieve more robust failure predictions and optimized maintenance planning.

4 DIGITAL TWIN IN PREDICTIVE MAINTENANCE

Digital twins allow for the real-time monitoring and simulation of physical assets. Optimal maintenance procedures can be recommended by AI systems that keep an eye on these digital twins, detecting performance issues before physical equipment has any problems [29][30]. These are made by reproducing the system's behaviour using data collected from the real thing. Then, they feed back to the physical process with information about potential outcomes, such error and defect forecasts or component maintenance.

1.4 Applications of Digital Twin

The production sector is changing quickly. Consequently, there is a growing interest among manufacturers in utilising technology like Digital Twins [31]. Technology based on digital twins has the ability to completely transform the industrial business and has enormous promise for many different applications.

- **Application Domain:** The aims and scope of the digital twin's implementation can be defined, allowing for the identification of the components that should be part of the transformation process [32]. One of the best things about digital twins is how accurate it is. Thus, by removing unnecessary features and components, and save time and effort and lessen the likelihood of making mistakes.
- **Data Points:** Twins of products, processes, or systems may or may not be necessary depending on the decision or control objectives. Along these lines, it's possible to specify the tools and methods that required, including deciding whether the digital twin should mimic the system's observed behaviour or its current state.
- **Technology:** Consideration of the identified data points and the intended method of information provision by the digital twin should inform the selection of appropriate technology. For example, if the use case is constrained by time, money, or business requirements, visualisation might not be necessary [33].

1.5 Digital twin technologies

Digital twins primarily focus on three areas: data collecting, data modelling, and data application. A digital twin is an electronic representation of a physical item created by merging four technologies: real-time data collecting and storage, virtual prototyping, object scanning, and information capture for insightful analysis [34]. The IoT, AI, XR, and Cloud are all examples of such technologies (Figure. 5)

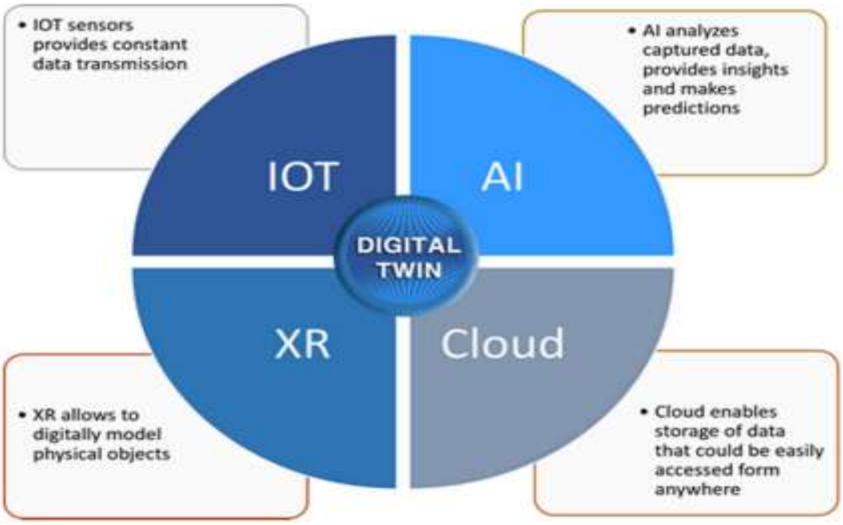

Figure 5. Technologies of Digital Twins.

- **Internet of Things (IoT):** IoT is a big network of "things" that are all linked together. Interactions between things, people, or people-things are what the connection is all about [35]. Digital twins rely on the IoT for all of their technological needs.

Nearly all IoT platforms able to do Digital Twinning by 2027. The IoT gathers information from physical items by use of sensors. can make a digital copy of a real-life item using the information sent by the Internet of Things.

- **Cloud Computing:** "Cloud computing" refers to the delivery of services through a networked, internet-based platform. This technology allows for efficient data access and storage over the Internet. Data processing and storage capabilities are made available to Digital Twins through cloud computing. The ability to access and store vast quantities of data from any location with an internet connection is made possible by cloud computing, which Digital Twin may utilise.
- **Artificial Intelligence (AI):** AI is a subfield of computer science that studies how to simulate human intellect in artificial systems. Some areas of artificial intelligence include robotics, image recognition, and language recognition. Digital Twins can benefit from AI through NN, ML, DL, and expert systems since AI can automatically analyse collected data and give useful insights, predictions regarding results, and advice on how to avoid possible issues.
- **Extended Reality (XR):** Virtual reality, augmented reality, and mixed reality are all forms of immersive technology that are encompassed by this phrase. Thanks to these advancements, the divide between the physical and digital realms can shrink, and our view of the world can grow. The aim of the AR is to create the digital representations of the physical objects which are able to interact with each other in real-time. Digital twins are the digital models of real-world items in which people can interact digitally using XR capabilities.

5 LITERATURE REVIEW

The section is a review of the literature on smart manufacturing techniques of predictive maintenance using AI, ML, the IoT, and digital twins. Its strategies lay on the concept of real-time fault monitoring, intelligent decision support, and secure interchange of data all of which aim at minimizing downtimes and ensuring optimization of its operations.

Putteti et al. (2025) In this section, the literature on the predictive maintenance strategies of smart manufacturing using AI, ML, IoT and digital twins is discussed. The solutions are tailored toward the minimalization of downtime and the maximisation of performance through the use of real-time fault detection, an adaptive decision-making process, and safe data transmission. Data sharing via a blockchain-based method means the security and privacy of data, as well as ease of exchange between IIoT systems [36].

Park et al. (2025) Focused on the urgency of failure detection and condition-based maintenance (CBM) in the semiconductor industry, the use of Fault Detection and Classification (FDC) systems and ML in equipment logs to predict equipment state and pre-emptive maintenance. Activities focus on the development of data engineering specialists, addition of depth in data analysis and equipment monitoring. In addition, it is the necessity to further the field since the current needs to be supplemented by new and improved sensor technologies, which should be closely related to the equipment manufacturers [37].

Baroud and Yahaya (2024) Introduced an innovative multi-agent-based framework that has the potential to revolutionize PdM in manufacturing, by empowering the artificial ML models to learn collaboratively. The framework leverages a multi-agent systems (MASs) solution to improve the integration, coordination and optimization of multiple ML models to enable adaptive decision-making. The framework is directly used in hydraulics in the Oil and Gas industry (OGI) and little has been done in terms of MASs and ML in this part. The new design is likely to increase the responsiveness of the system and decision support processes that will result in more intelligent, proactive maintenance strategies [38].

U A et al. (2024) Offering an AI-powered predictive maintenance model that is specifically adapted to smart factories and their non-stationary environment, the ever-changing operational conditions they have to deal with, and a real-time demand to make decisions. Recurrent failure to get the right maintenance time and unexpected breakdowns are the outcomes of conventional predictive maintenance systems that are dependent on the inflexible models trained over historical data that limits the scope of further actions in the event of changes in equipment behaviour and changing environmental levels. It puts into focus a hybrid architecture that encapsulates deep learning that encapsulates feature extraction, reinforcement learning that makes adaptive decisions, and transfer learning to reuse learning across domains [39].

Piyush et al. (2023) The proposed study introduces a new PdM framework dedicated to automated washing machines, which addresses unique challenges in the area of study. The study categorizes PdM application within the industry per the ML/DL application, but focusing on KPIs. The new trends in deep learning have presented innovative algorithms which might transform PdM. The application of unsupervised learning to those cases where a small amount of previous examples is available and the role of fault identification in cost savings both are emphasized. This is because the proposed solutions would result in less downtime, more equipment that could be used and more sustainability by increasing the life of many of the key units on the machines [40].

Babu et al. (2023) Discussed a variety of industrial-related applications of the IoT, challenges, and trends. In this study, businesses opportunities, approach, wisdom and technicalities of better maximizing manufacturing operations are excavated through keen analysis of relevant literature. The use of IoT to analyse data, to optimise supply chains, monitor in real-time, carry out predictive maintenance and automate is critical. In addition, the review focuses on how the IoT affects energy conservation, monetary savings and the surroundings [41].

Qamsane et al. (2022) Examined and discussed a DT Framework consideration to monitor the effectiveness of process manufacturing systems to prevent unscheduled downtime which is a frequent occurrence and reduces the profitability of an industry. An OPA testbed can be used to demonstrate the DT framework that helps to easily gather and analyse process manufacturing line data. Providing a solution to use new system-wide DT solutions to ensure that other vital steps are not bypassed, the proposed DT framework solution has been developed, so it will be possible to avoid stopping production and spending an excessive amount of money on research and development without hampering the ability to introduce system-wide DT solutions. [42].

Table II presents recent predictive maintenance studies with a focus on AI, IoT, and digital twin. Complexity, scaling, and data quality stand out as ones of the greatest challenges and the main activities in future work are the broader adoption, interoperability, and integration of AI into real-time processes

TABLE II: SUMMARY OF PREVIOUS STUDY ON SMART MANUFACTURING

Reference	Study On	Approach	Key Findings	Challenges / Limitations	Future Directions
Putteti et al. (2025)	Intelligent Industrial IoT (I-IIoT) for smart manufacturing and PdM	Edge computing + AI + big data analysis; ML & DL for fault detection; cloud–edge hybrid processing.	Real time data processing reduces delays; secure and smooth IIoT communication; improved equipment failure prediction	Implementation complexity due to hybrid architecture and blockchain integration	Scale to diverse industrial domains; improve interoperability and standardization
Park et al. (2025)	Failure detection & CBM in semiconductor manufacturing	Fault Detection & Classification (FDC) with ML-based log analysis; emphasis on data engineering expertise	Early detection of equipment conditions enables timely maintenance; improves equipment monitoring depth	Need for advanced sensor technology; dependency on skilled data engineers	Collaboration with equipment manufacturers; develop next-gen sensors
Baroud & Yahaya, (2024)	Multi-agent-based PdM framework for hydraulic systems in Oil & Gas	MASs for ML model coordination & optimization; collaborative learning	Enhanced integration of multiple ML models; adaptive decision-making for better responsiveness	MAS applications in PdM are underexplored; requires coordination between multiple agents	Extend MASs to other industries; explore cross-domain collaborative learning
U A et al. (2024)	Adaptive AI-based PdM for smart factories	Hybrid AI: DL for feature extraction, RL for dynamic decisions, TL for cross-domain adaptation	Better adaptability to changing conditions; reduces unexpected failures	Complexity in integrating DL, RL, and TL; computational overhead	Develop lightweight adaptive models; real-time learning at the edge
Piyush et al. (2023)	PdM for automatic washing machines	ML/DL methods for defect detection; performance indicator-based categorization; unsupervised learning.	Improved downtime reduction, equipment availability, and sustainability	Limited historical data in some cases; performance depends on data quality	Explore more unsupervised/semi-supervised methods; expand to other appliances
Babu et al. (2023)	IoT applications in industrial manufacturing	Literature review on IoT automation, monitoring, PdM, supply chain optimization	IoT improves automation, monitoring, maintenance, and sustainability	Adoption challenges in legacy systems; integration with existing processes	Focus on energy management, cost reduction, and environmental impact
Qamsane et al. (2022)	Monitoring process manufacturing performance with a digital twin (DT)	DT framework with OPA testbed for non-intrusive system evaluation	Avoids unplanned downtime; enables testing DT solutions without disrupting production	Limited to testbed scenarios; scalability to large-scale operations needs validation	Scale DT framework to full production lines; integrate with PdM and AI

6 CONCLUSION AND FUTURE WORK

PdM has disrupted the production philosophy of predictive maintenance and helped companies change their asset management strategies to a proactive approach rather than reactive and preventive. ML, digital twins, and Industrial IoT technologies, can, through PdM, enhance fault detection, failure prediction, and decision-making, which reduces downtime, increases the life time of equipment, and minimizes resource utilization. Literature highlights a variety of frameworks, including edge–cloud hybrid architectures, adaptive AI models, and multi-agent coordination, tailored to diverse industrial needs. These advancements have demonstrated significant success in enhancing real-time responsiveness, operational efficiency, and maintenance accuracy. However, challenges such as scalability, implementation complexity, sensor limitations, and legacy system integration persist. Overcoming these issues is essential for achieving fully autonomous maintenance ecosystems.

Future research should focus on lightweight, adaptive AI models for efficient operation in edge environments, ensuring real-time monitoring and decision-making without heavy computational demands. Improving interoperability standards will also be vital for seamless PdM integration across varied platforms and domains. Transfer learning and cross-domain adaptation can further strengthen flexibility, enabling models trained in one setting to be applied in another. Moreover, combining PdM with self-healing systems and automated execution can advance industries toward autonomous manufacturing. Expanding PdM into healthcare, energy, and infrastructure will broaden its impact and support sustainability goals.

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