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Predictive Maintenance in Smart Manufacturing: A Review of Machine Learning and Digital Twin Approaches

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Abstract: Predictive maintenance has emerged as a new method to smart manufacturing, allowing firms to forsake reactive and preventative approaches to equipment management based on data analysis. The current study conducts a thorough analysis of digital twin and ML technologies, which jointly aid in the prediction of remaining useful life, defect identification, and anomaly detection in a variety of industrial contexts. Machine learning techniques are scalable, adaptable in nature, and digital twins enable the building of synchronized virtual models that represent the behavior of the physical assets continually delivering real-time information about the deterioration trends, and available systems behavior. Integration of these technologies will facilitate better reliability, less downtime and better use of resources. Nonetheless, literature shows that there are several difficulties such as the inconsistency of sensor data, constraints of the heterogeneous systems interoperability, and issues of model interpretability and industrial implementation. The review notes a necessity of more integrative frameworks that would combine multi-source industrial information with dynamic and continuously learning models. By combining the current advancements, limitations, and implementation gaps, this study will provide a thorough understanding of how predictive maintenance is evolving in smart manufacturing. It also recognizes new opportunities of more autonomous, intelligent, and resilient maintenance ecosystems that can sustain future Industry 4.0 and Industry 5.0 ecosystems.

Keywords: Smart Manufacturing, Predictive Analytics, Machine Learning, Digital Twins, Industrial Automation, Maintenance Optimization.

1. Introduction

Smart manufacturing (SM) is a forward-thinking production system that uses digital technology, information systems, and networked data to optimise manufacturing processes. It focusses on real-time decision-making, adaptability, and efficiency in contemporary industries. Industry 4.0 has only accelerated this transformation by mixing IoT, cyber-physical systems (CPS), Could Computing, and AI into a more traditional manufacturing process [1]. Such technologies allow constant monitoring, predictive analytics, and automation of production lines. The aspect of equipment reliability is the main focus in SM because failure may result in high downtimes, loss in production, and safety risks. Therefore, good maintenance plans will be essential in improving the efficiency of operations, cost reduction and maintaining safety in manufacturing facilities. There are reactive, preventive, and predictive maintenance strategies used in manufacturing. Reactive maintenance reacts to a breakdown after it occurs, which typically outcomes in significant downtime and repair costs [2]. Preventive maintenance has routine maintenance schedules that consider time or usage schedules that may give rise to unnecessary maintenance or even failure.

Predictive maintenance (PdM) has proven to be a more effective substitute, and it uses data-driven insights to forecast equipment health and optimize the maintenance timeline. PdM can be used to achieve the objectives of smart manufacturing by minimizing unexpected downtime and increasing resource usage[3]. Predictive maintenance combines sensor, monitoring, and analytics systems, which analyse sensor data to evaluate the health of equipment and forecast future failure before it happens. This is a proactive strategy that enables manufacturers to plan on how to perform maintenance activities in the most optimal moment that reduces the number of interruptions and prolong the lifespan of the most important assets. The most important enabling technologies are the IoT sensors in data collection, real-time monitoring systems, and advanced analytical platforms. PdM has significant advantages, most of which are increased productivity, lower cost of operation and a higher overall reliability of the system.

ML offers an ability to analyze a huge amount of manufacturing data in order to identify anomalies, forecast failures, and optimize maintenance processes. Regression, classification, clustering and deep learning, among others, are some of the techniques employed to model equipment behaviour and predict faults[4]. Nevertheless, there are still issues to be addressed, such as the quality of data and their high dimensionality, model intelligibility, and scalability in complex systems. Digital twins represent real-world object representatives and open possibilities of monitoring, simulation and predictive analytics[5]. Digital twins coupled with ML can be used to provide benefits to predictive maintenance, such as scenario testing, enhancing the accuracy of fault detection, as well as assisting in proactive decision-making. ML and digital twins offer a strong model of intelligent maintenance, which boosts the efficiency of operations, minimises risks, and simplifies the creation of the new production system.

1.1. Structure of the Paper

The following format will be used for the paper Section II defines the idea of predictive maintenance and its significance, and how the strategies of maintenance will develop with Industry 4.0. Section III addresses machine learning methods and advantages and its use in predictive maintenance. Section IV presents the foundations of digital twins and their application in design, production, and maintenance. Section V provides the current literature, which gives a synthesized account of previous studies. Section VI is the conclusion of the work and noted future research directions.

2. Understanding Predictive Maintenance

Predictive Maintenance is the kind of topic that needs to be researched in relation to its purpose, technological basis as well as its evolutionary process as compared to the traditional methods of maintenance. The article points to the fact that smart manufacturing is based on real-time data, sensors, and IoT connectivity to forecast failures and lessen the time-wasting in the unnecessary downtime. It also explains how reactive, preventive, and condition-based models transformed to be fully predictive models that Industry 4.0 integration and smart monitoring can support.

2.1. Importance in Smart Manufacturing

An developing method of preventative maintenance called predictive maintenance (PdM) seeks to improve industrial processes' performance and efficiency by extending equipment life and guaranteeing sustainable operational management [6]. On the one hand, by offering the possibility to implement interventions with the help of failure prediction, this means reducing the downtime and the number of unnecessary stopovers, as well as a reduction in the cost of the repair. Manufacturing businesses are implementing sophisticated predictive maintenance solutions. This is accomplished by enabling the tracking of equipment failures remotely and in real-time, as well as by estimating the remaining life of the failing components. The later should be diagnosed and identified to ensure that the equipment works properly [7]. The latest form of maintenance is the predictive maintenance which provides the cheapest, environmentally sustainable and durable equipment. Proactive maintenance is a maintenance practice that involves performing troubleshooting at the root. The maintenance approach is extremely successful when combined with predictive maintenance, hence it is gaining popularity.

2.2. Evolution of Maintenance Strategies

Maintenance as a concept in industrial settings has changed significantly with time. This transition can be traced to the simplistic practices of failure-responses to elaborate data-driven approaches. The development of reactive to predictive maintenance has been influenced by the growing automation, the complexity of equipment and the development of sensing and computational tools.

2.2.1. Reactive Maintenance

The original and simplest kind of maintenance plan was reactive maintenance, sometimes known as run-to-failure. In this model, machines are run up to the point of failure, and then the process of repair is not taken until they fail[8]. Even though it needs negligible planning and no on-going observation reactive maintenance normally results in Unexpected production downtime, Higher costs of repairing the components due to serious failures, Reduced equipment life and increased operational and safety hazards.

2.2.2. Preventive Maintenance

As industries expanded and the expense of downtime escalated, a more systematic approach known as preventative maintenance was established. It is a strategy of planned maintenance that sets the maintenance time at specific time intervals, usage or manufacturer recommendations irrespective of the actual health condition of the equipment[9]. Preventive Maintenance provides Less unforeseen equipment breakages, Increased operating dependability and increased equipment service life. Nevertheless, preventive maintenance can also lead to over servicing, unnecessary replacement of parts, and loss in productivity, caused by scheduled shutdowns.

2.2.3. Condition-Based Maintenance

The technology of sensing and monitoring allowed the establishment of condition-based maintenance. In this method, equipment condition in real time is assessed by considering the parameters like level of vibration, temperature, lubrication quality, and acoustic features. Maintenance is also done on when there are indicators that there is degradation of performance or imminent failure. Condition-based maintenance offers more effective resources in maintenance allocation, Less unnecessary maintenance intervention and increased reliability and equipment availability.

2.2.4. Predictive Maintenance

The most advanced stage of maintenance development is predictive maintenance, which uses prognostic modelling, ML, and data analytics to forecast failure likelihood and remaining usable life . Predictive maintenance brings together condition monitoring and analytical forecasting to make Failure prediction before it happens, optimized and minimally disruptive maintenance scheduling, increased equipment uptime and operational continuity and a Significant reduction in maintenance and lifecycle costs.

2.3. Industry 4.0 smart manufacturing concept

Industry 4.0 will combine CPS, IoT connection, automation, and Advanced Analytics to create smart and responsive industrial systems. The Figure 1 illustrates this notion with the illustration of how cloud computing, smart sensing, big data analytics, and digital control layers interconnect in order to make production processes interdependent. Industry 4.0 encourages machine-to-machine communication, decentralized decision-making, and system integration of the lifetime of a system, including design and prototype to monitoring, control, and scheduling.

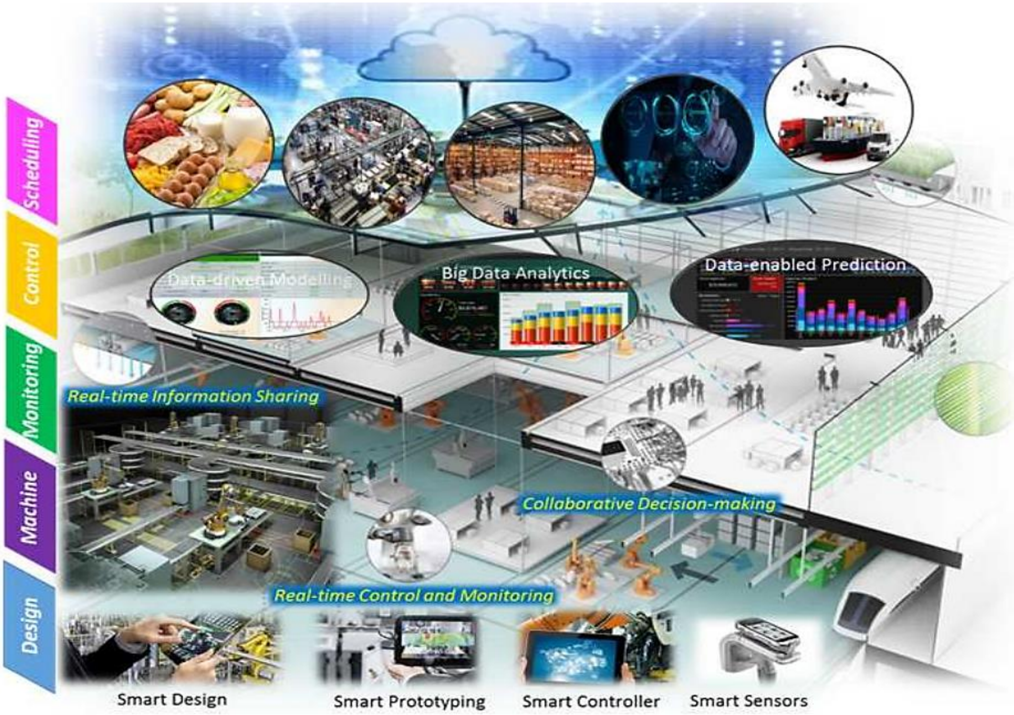

Figure 1: A Concept Framework of Industry 4.0 Smart Manufacturing System[10]

The Figure 1 represents an example of a digitally connected intelligent manufacturing environment provided by automation, data intelligence, and system interaction.

- Supply Chain integration: The integrated smart manufacturing system that contains design, machines, monitoring and control layers that work together to increase productivity and automation.
- Real-Time Data and Monitoring: It emphasises real-time monitoring and control of industrial processes using smart sensors and controllers, as well as a continuous flow of data.
- Data-Driven Analytics and Prediction: The top section illustrates data-driven modelling, big data analytics and predictive functionality which converts operational data into information to aid in optimisation of decisions.
- Collaborative and Cloud-Enabled Operations: It represents cloud integration, exchange of information and collaborative decision-making among various sectors of the industrial sector, which facilitate synchronized and smart factories.

3. Machine Learning Approaches in Smart Manufacturing

An application of machine learning in Smart Manufacturing is explained in terms of its analytical advantages, types of algorithms, and benefits of performance. The discussion describes how a pattern can be revealed through supervised, unsupervised, and semi-supervised approaches that can be used to make reliable decisions in maintenance and improve quality control. The value of ML is proven by practical industrial application.

3.1. Machine Learning Techniques

The implementation of ML in the production process aids in enhancing production procedures and making the process more efficient. ML is an intelligent technology that increases the operation of machines in the production facilities via the utilisation of production data. ML is a branch of AI which employs statistical approaches to allow computer systems to learn by analysing data without a program being presented to them[11]. Many functions such as prediction, classification, clustering, and optimization can be performed with the help of ML. ML programs identify areas of attention within the manufacturing process in order to gather data and provide working ideas on changes.

The application then provides algorithms with the information necessary to promote learning[12]. The robots may repeatedly learn and improve procedures when this process is initiated, without the need for human personnel to program them. Manufacturers are able to start improving and growing their businesses by using the data collected by ML systems to make better manufacturing decisions. The ML algorithms are sorted as four varying definitions, which include Supervised Learning, Unsupervised Learning, Semi-supervised Learning and Reinforcement Learning (Figure 2).

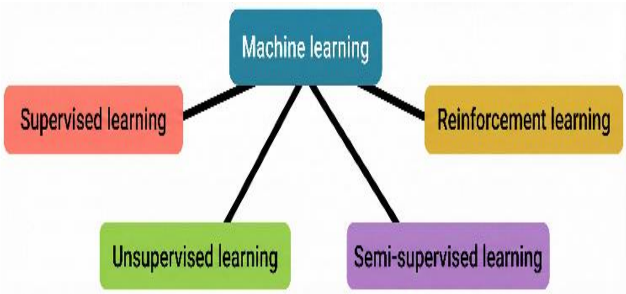

Figure 2: Ml Techniques

The Figure 2 outlines the better support techniques of the smart manufacturing as follows:

3.1.1. Supervised Learning

Supervised Learning makes use of labelled data, in which an input has a known output. Through such instances, the algorithm uses the input attributes to determine the correct output. It has classification (predicting discrete classes) and regression (predicting continuous values). Some of the common supervised algorithms are linear and LR, NB, KNN, DT, RF, and XGBoost.

3.1.2. Unsupervised Learning

Unsupervised learning determines the concealed trends in unmarked information. It is applied to acquire structures or relations in datasets. Key ones are clustering, dimensionality reduction, density estimation and anomaly detection. Examples of unsupervised algorithms are stacked auto-encoders (SAE), k-means, k-medoids, and fuzzy c-means.

3.1.3. Semi-Supervised Learning

Semi-supervised learning improves learning performance by combining labelled and unlabelled data. Key approaches include:

- Self-training: Self-labelling of unlabelled data in stages.
- Graph-based techniques: labels distributed amongst the graphically connected data points.
- Co-training: Co-training is used between more than two models.

Multi-view learning - combination of multiple data views.

3.2. Advantages of Machine Learning in Smart Manufacturing

ML provides high potential which can be used to transform the conventional production mode into a smart, data-oriented and efficient production technology. The key advantages include:

- Better Predictive Maintenance: ML identifies early equipment failure trends and forecasts remaining useful life, eliminating the occurrence of unplanned downtime[13].
- Improved Product Quality: Models detect errors and streamline the process parameters that lead to more reliable and consistent product output.
- Real-Time Decision Support: ML examines sensor and IIoT data in real-time, providing prompt reactions and smarter production changes.
- Improved Operational Productivity: Automation of workflows, energy consumption, and resource distribution leads to improved productivity with reduced wastage.
- Reduction of Costs within Processes: The reduction in maintenance costs, decrease in quality, and interruptions in production result in a lot of financial savings.
- Assists Intelligent and Autonomous Manufacturing: ML makes it possible to have adaptive control, integrate robotics, and self-optimizing systems in accordance with Industry 4.0 objectives.

3.3. Applications in Smart Manufacturing

ML applications in the predictive maintenance as summarized in Table I have been applied across various industries and have used neural networks, classification, Bayesian and prognostic models to facilitate early fault detection, failure prediction, reduced downtime and proactive maintenance decisions.

Table 1: Machine Learning Applications in Predictive Maintenance

References	Equipment	ML Model	Role of PdM	Data	Key Findings
[14]	CNC milling machine	Artificial Neural Network (ANN)	Tool wear monitoring; retrofitting legacy machines for predictive maintenance	Acceleration data from programmable prototyping sensor platform	Demonstrated feasibility of retrofitting older machines for Industry 4.0 using ML and sensor data
[15]	Premium printing equipment	ML classification algorithm	Forecasting machine downtime; predicting imminent failures	Historical machine data	Provided real-time failure prediction; highlighted challenges and lessons learned; limited by sensor availability
[16]	Semiconductor manufacturing line	Bayesian-based failure probability modeling	Early failure prediction; proactive maintenance planning	Event-driven maintenance data	Bayesian network identified failure signatures and critical regions, enabling earlier predictions than traditional methods
[17]	Complex vending machines	Binary classification + two-stage multi-class prognostics model	Automated diagnostics and prognostics to reduce maintenance costs	Machine logs, performance logs, system logs, maintenance reports	Achieved over 80% accuracy; two-stage prognostics model outperformed conventional single-stage approaches

4. Digital Twin Technology in Predictive Maintenance

Digital Twin technology has been described as a virtual analogous to the physical property to allow ongoing interaction between simulated and real systems, data fusion, synchronized updates and cyber-physical alignment enhance prediction accuracy and operational insight.

4.1. Concept of Digital Twins

The term Digital Twin was introduced by Grieves [18]. Virtual representations of actual items are often created digitally to simulate their behaviours within real-world limitations. This implies that the Digital Twin consists of three components: actual goods in the Physical World, Virtual Models in the Virtual World, and connected data that links the two worlds. The Digital Twin reflects the two-way dynamic mapping between virtual models and real-world objects. In particular, it is tangible items that are becoming virtualised. Virtual refers to the assessment, forecasting, prediction, and optimisation of the physical operating process. Accordingly, it is the realisation of a virtual process[19].

After product design, production, and maintenance processes have been simulated and optimised, the physical process is guided to implement the optimal solution. Data convergence is a natural step in the communication process between virtual and actual worlds. Sensors are used to transfer data from the physical world to virtual models, allowing for simulation, validation, and dynamic adjustment. And the simulation data is returned to the physical world in response to the change and advancement of the functioning and value addition. It can only be cross analysed in a convergent data environment.

4.2. Digital Twin–Based Predictive Maintenance

The foundation of digital twins is computer science, data science, production engineering, and information science. Four pillars of core foundations can be concluded to be enabling pillars:

4.2.1. Modelling, Simulation, and VV&A

The Digital Twin modelling integrates physical, virtual, connection, data, as well as service models to reflect real systems. Simulation theories facilitate structural, behavioural and operational analysis, whereas verification, validation and accreditation are used to guarantee the fidelity of models through the evaluation of errors in algorithms, hardware and representation. These bases facilitate the fact that virtual entities are very realistic on how to predict maintenance based on physical assets.

4.2.2. Data Fusion

Data fusion involves the integration of physical sensor data with virtual model data and past data in form of pre-processing, mining and optimization[20][21]. Rule-based reasoning techniques, fuzzy analysis, clustering, and dimensionality reduction techniques allow the formation of patterns of degradation and indicators of machine health. It is this pillar that assists in predictive analytics to demonstrate lifecycle evolution trends.

4.2.3. Interaction and Collaboration

Digital twins are also based on coordinated interaction between physical and virtual systems and hybrid cyber-physical spaces. The processes of interaction make it possible to coordinate decision-making, responsive control to disruptions, and real-time notifications, which shape the foundations of autonomous maintenance interventions[22].

4.2.4. Service Orientation

Theories on services include encapsulation service, QoS measurement, service matching, optimal service and fault tolerant management. Such frameworks make it possible to implement condition-based servicing, failure diagnostics, maintenance planning, and operational recovery paths, which creates the connection between information on prediction and actionable maintenance plans.

4.3. Applications of Digital TwiniIn Manufacturing

Digital Twin unifies all production processes, as depicted in Figure 3, and they may realise the closed loop and optimisation of the Product Design, manufacturing, and smart MRO, etc.

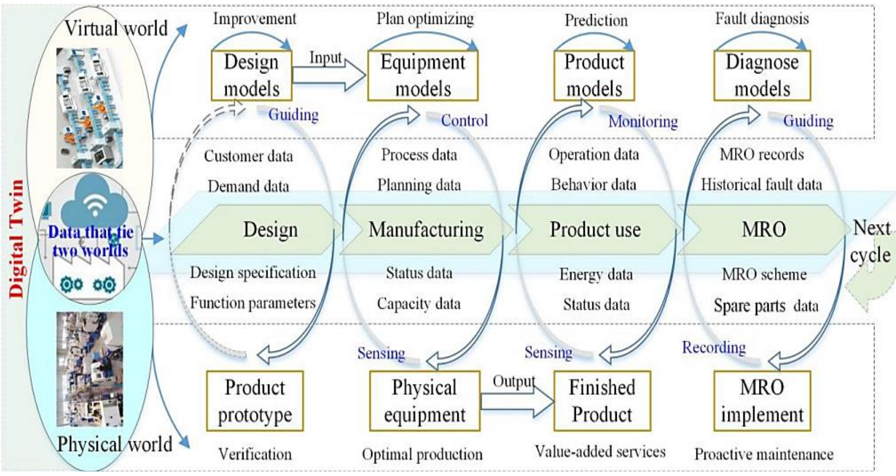

Figure 3: Digital Twin In Smart Manufacturing[23]

4.3.1. Digitaltwin-Based Product Design

Digital twins allow the virtual depiction of a product connecting the intent of the designer to real-life limitations. This helps in the refinement of design, quick verification of designs and manufacturability and early identification of design problems, eliminating the need to use physical prototypes and shortening the time to create personalized products.

4.3.2. Smart Manufacturing in Digital Twin Workshop/ Factory

After the design is completed, it is produced in a smart factory where virtual models are used to simulate resources, workflows and process dynamics. The synchronization of physical and digital space in real-time is capable of providing consistent monitoring capabilities, rapid problem detection, and optimization in response to environmental changes to achieve greater efficiency, accuracy, and product quality.

4.3.3. Product DigitalTwin for UsageMonitoring

A product-level Digital Twin collects real-time use and environmental data, which is then utilised to monitor the system's status throughout operation. The virtual model can predict the remaining life or future faults and can be used to make condition-aware control, and proactive decisions about operations under various conditions, which is simulated in the virtual model.

4.3.4. DigitalTwin as Enabler for Smart MRO

Digital twins allow predictive and corrective maintenance this is achieved by fault visualization, root-cause analysis and VR/AR testing of repair strategies. Maintenance measures are designed and checked in digital form prior to the implementation whereas lifecycle information is stored to support future enhancement of the product.

5. Literature Review

The literature reviewed reflects the progress that has been made in predictive maintenance by utilizing Machine Learning and Digital Twin technologies, focusing on smart manufacturing development and leaving a gap in integration, real-time implementation, scalability, and industrial validation.

Aivaliotis, Georgoulias and Chryssolouris, (2019), argue that the RUL of the machines may be calculated using the Digital Twin idea and physics-based simulation models. This method enables predictive maintenance through PHM methods. The methodology consists of the modelling of resources in a computerized setting that mimics the actual behaviour of resources and collects data of machine controllers and sensors to tune. Simulation results evaluate machine conditions and compute RUL, which can be monitored and predicted in a non-invasive manner. A case study on an industrial robot demonstrates how the technique is justified[24].

Carvalho et al. (2019) discuss how the amount of data acquired throughout the production process is growing tremendously as a result of the advancement of sensing technology. Data processing and analysis will provide important information about manufacturing systems and equipment. One of the areas is equipment maintenance, which influences the efficiency of the operations and aims to avoid the cases of production stops by identifying and eliminating faults. ML has emerged as one of the most promising Predictive Maintenance (PdM) applications for preventing equipment failure. The article shows the systematic literature review of the ML techniques in PdM, providing a detailed account of the techniques used, their effectiveness, challenges, and prospects, which facilitates future studies in the field[25].

Qi et al. (2018) highlight the function of Digital Twin technology in supporting cyber-physical integration in production. The authors argue that smart manufacturing services can enhance business processes and operational procedures, ultimately leading to increased productivity. The synergy between smart manufacturing services and digital twin technology is poised to transform multiple aspects of the manufacturing domain, including Product Design, manufacturing processes, usage, maintenance, repair, and overhaul (MRO). This integration supports greater manufacturing planning and production management by a two-way connection among the virtual and physical domains of manufacturing. The paper emphasises the convergence of Digital Twin and manufacturing services by detailing the various components of Digital Twin that manufacturers employ as services[26].

Kritzinger et al. (2018) examine a concept of the Digital Twin (DT) as a critical facilitator of digital transformation, noting a lack of consensus in its definition across various fields. The purpose of this work is to provide a categorical literature evaluation of DT, especially in manufacturing, by classifying previous papers according to the degree of DT integration. The Digital Model (DM), Digital Shadow (DS), and the Digital Twin are distinguished. Findings suggest that literature relating to the most advanced growth stage, the DT, is scarce, but there is a more considerable corpus of study focussing on DM and DS[27].

Tao & Zhang (2017) emphasise the evolution of a smart manufacturing age based on advancements in IT such as Cloud Computing, IoT, Big Data, and AI. National goals such as Industry 4.0 emphasise an integration of the physical and virtual production universes in order to deliver intelligent manufacturing processes such as connectivity and control. The idea of a Digital Twin Shop lour (DTS), which consists of 4 main components a Physical Shopfloor, a Virtual Shopfloor, a Service System, and Digital Twin data is put out as a means of achieving this convergence. The paper also looks at how it works, how it can be implemented, major technologies and the challenges that are involved in DTS.[28].

Negri, Fumagalli & Macchi (2017) discuss the notion of Digital Twin (DT), one of the core ideas of the Industry 4.0 era. The system is extensively applied both in industry and in research but it is difficult to find a single definition in scientific literature. The paper will trace the history of DT since its formation in the field of aerospace through modern use in manufacturing and smart manufacturing studies. DT consists of developing virtual models of systems within their lifecycle and supporting real-time data synchronization through sensors to improve the process of making decisions. It also provides a definition of DT to Industry 4.0manufacturing, based on the EuropeanH2020 MAYA project[29].

The key studies presented in Table II are compared in terms of focus, approaches, findings, advantages, limitations, and future directions, which demonstrate that the missing convergence between the ML and Digital Twin in PdM of smart manufacturing can be achieved.

Table 2: Research Gap of Existing Ml-Based and Digital Twin-Based Predictive Maintenance Studies

References	Focus	Approaches	Main Findings	Advantages	Limitations / Gaps	Future Work
Aivaliotis, Georgoulias & Chryssolouris (2019)	Predicting Remaining Useful Life using Digital Twin within predictive maintenance	Physics-based simulation models aligned with real sensor data to evaluate machine degradation	Demonstrated that DT simulation can estimate RUL and monitor machine condition without intrusive diagnostics	Enhances maintenance planning, realistic modeling of machine behavior, supports PHM techniques	Requires high-fidelity modelling, limited adaptability across different machine types, lacks ML-based predictive enhancement	Integration of data-driven ML with DT for improved RUL accuracy, scalability to broader manufacturing systems
Carvalho et al. (2019)	Systematic review of Machine Learning applications in predictive maintenance	Comparative evaluation of MLmethods for maintenance optimisation, defect detection, and failure prediction	ML techniques show strong performance in predicting equipment failures and improving uptime in industrial environments	Helps identify suitable ML methods, supports data-driven maintenance decision-making	Does not address Digital Twin integration, relies mainly on literature examples, limited industrial deployment evidence	Combined ML-DT PdM frameworks, standardized benchmark datasets, real-world evaluation studies
Qi et al. (2018)	Digital Twin integration with smart manufacturing service systems	Connectivity in both directions between virtual and real-world production settings to maximise efficiency	DT-enabled service models can improve production planning, control, and lifecycle decision-making	Strengthens cyber-physical interaction, improves productivity and operational transparency	Limited focus on predictive maintenance application, minimal validation through case studies	Embedding predictive maintenance analytics into DT services, linking with ML-driven condition monitoring
Kritzinger et al. (2018)	Classification and conceptual clarification of Digital Twin maturity levels	Differentiation of DigitalModel, DigitalShadow, and full DigitalTwin in manufacturing contexts	Found that most published work remains at lower development stages, with true DT implementations being rare	Provides useful categorization for understanding DT progression, clarifies terminology for researchers	Does not explore predictive maintenance usage or ML integration, lacks application-oriented insights	Mapping DT maturity to PdM capabilities, guidelines for progressing toward functional DT systems
Tao & Zhang (2017)	Digital Twin Shop-floor (DTS) for smart manufacturing environments	Framework with physical shop-floor, virtual shop-floor, service system, and real-time DT data	Enables synchronized monitoring and interactive control of manufacturing processes	Establishes foundational architecture for smart shop-floor digitalization	PdM not explicitly modeled, challenges in real-time data integration, lacks predictive analytics	Incorporating ML-based predictive maintenance into DTS, improving interoperability and data fusion
Negri, Fumagalli & Macchi (2017)	Evolution and definitions of Digital Twin in Industry 4.0 manufacturing	Literature-based conceptual analysis linking DT to lifecycle optimization and smart	DT provides synchronized virtual representations that support decision-making	Clarifies DT meaning across disciplines, aligns DT with smart manufacturing	No empirical performance results, does not apply DT to predictive maintenance,	Developing DT frameworks tailored to PdM, integrating data-driven techniques,

		factory operations	and operational optimization	strategies	lacks connection to ML approaches	validating in industrial environments

6. Conclusion and Future Work

Increased industrial connectivity, data acquisition and computational intelligence is transforming the manner in which manufacturers operate to manage the care of assets health and operational survivability. By combining predictive maintenance with machine learning methods, it allows the systems to understand the behaviour of equipment better, detect issues early, and plan interventions earlier than the failure will affect the production. Environments with digital twins enhance this even more as they provide a reflection of the physical assets within dynamic virtual environments (where complex behaviours can be simulated, assessed and optimised prior to real implementation). Combined, all these technologies contribute to more resilient manufacturing processes, long-lived machinery, as well as data-driven decision-making, which corresponds to current Industry 4.0 objectives. In the future, a number of research opportunities can be combined to enlarge the predictive maintenance capabilities. The challenge is to come up with unified frameworks that combine the use of ML algorithms with that of digital twins in a loop. Future research ought to be on adaptive learning model that can dynamically learn as conditions change. The federated and privacy-preserving learning exploration would improve data security and make industrial sites cooperate. More practical virtual world with physics based modelling and constant sensor feedback will enhance predictive accuracy. Lastly, increased automated maintenance planning using autonomous agents and reinforcement-learning controllers can be used to establish entirely self-regulating manufacturing ecosystems.

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