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AI-Based Predictive Maintenance Systems for Smart Manufacturing: A Review and Future Outlook

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Abstract: Predictive maintenance (PdM) is one of the enabling technologies of smart manufacturing in which artificial intelligence (AI) is used to predict equipment troubles, or even better anticipate the failure of equipment, based on sensor data, machine learning algorithms, and digital twins. The traditional techniques of maintenance such as the reactive maintenance technique and the preventive maintenance technique will most probably introduce undue downtimes, wastages or redundancy. In comparison, AI-oriented predictive maintenance is a combination of real-time data analytics, industrial internet (IIoT), and existing deep learning technology will allow equipment to operate 24/7, minimize the risk of operations, and make decisions. It is a review article on the use of AI-based predictive maintenance in smart manufacturing. It talks about the establishment of PdM, how AI can develop real-time faults and use machine learning, deep learning and deep reinforcement learning procedures. Providing the advantages of PdM systems, the list below states with comment of automatic saving in case of downtime, of low cost and sustainability of aerospace case, case of automotive and case of energy. The issue of the heterogeneity of the data, non-standardization, threat to cybersecurity, and explainable AI is solved. Predictive maintenance and its combination with Industry 4.0, such as digital twins, edge computing, and blockchain, is another item on the list of the ways to make manufacturing systems more autonomous and resilient. The paper ends with a definition of future directions that include hybrid AI model, federated learning of collaborative PdM, and explainable AI model of trust and adoption. Smart manufacturing ecosystems can enable all this by adding intelligence to maintenance to move to more sustainable, reliable, and adaptable operations as defined in Industry 5.0.

Keywords: Predictive Maintenance, Artificial Intelligence, Smart Manufacturing, Industry 4.0, Machine Learning are some of the keywords that should be remembered.

1. Introduction

Smart manufacturing 4.0 Future: As the industrial system moves to smart manufacturing within the Industry 4.0 environment, the production system in the industry changes radically. As compared to the past where the manufacturing processes were mainly manual and human intervention oriented, Industry 4.0 uses convergence between cyber-physical systems, industrial Internet of Things (IIoT), cloud computing, big data analytics and artificial intelligence (AI) to design interrelated, intelligent, and autonomous manufacturing systems. It is also the type of integration that has given manufacturing systems real-time control opportunities, decision-making, industrial process optimization, flexibility, resiliency, and efficiency (Carvalho et al., 2019).

Practice Development of Maintenance: Predictive maintenance (PdM) is one of the most important applications of the change. Traditional approaches to maintenance, such as reactive maintenance, in which processes are only implemented once the equipment has failed, or proactive maintenance, in which a maintenance process is implemented on a regular basis and without consideration of the status of the equipment, are generally inefficient, either due to the cost of downtime, or due to the unnecessary replacement of components. Rather predictive maintenance is a control that will be made on the information data and not on the potential failures since predictive maintenance enables industries to think how to interfere before a specific situation takes place. It has minimised the unwanted downtimes, minimised the operation cost, maximised the machine life, and maximised scale efficiency and PdM is one of the key building blocks of intelligent manufacturing solutions (Zonta et al., 2020).

PdM as an Enabled PdM: The additional complexity of industrial equipment and the sheer amount of information produced by the available sensor technologies requires the implementation of more advanced computing methods to offer meaningful predictions in the field of maintenance. Artificial intelligence (AI) is the giant enabler in this regard. AI-based PdM systems represent a form of microprocessor that leverages heterogeneous or high-frequency sensor data, history of operation, and context data to infer unobservable trends and identify abnormalities and make accurate future failure predictions (Lee et al., 2018). This is in contrast with the conventional statistical systems which are not dynamic and can be expanded to a host of industrial structures as more data is pumped into the system and the system keeps on improving.

Machine learning/ Deep Learning position: Machine learning (ML) and deep learning (DL) are also techniques of relevance in the assistive maintenance AI domain.
Machine Learning (ML): Support-vector machines (SVMs), decision trees, and random forests are the most popular algorithms used in PdM applications to detect the existence of anomalies and classify them (Carvalho et al., 2019). They can also be used when dealing with structured industry information because of their interpretable models and relatively quick training.
Increased functional capabilities with Deep Learning (DL): Deep neural network (convolutional neural network (CNNs)) and long short-term memory networks can be trained to jointly learn interactions between complex

industrial data, vibration patterns and time-series data, in space and time (Zhang et al., 2019). They come in especially handy when working with a high-dimensional and unstructured stream of data such as Industry 4.0.

Purpose of the Review: This review describes the history and practice of predictive maintenance based on AI in smart manufacturing, outlines methodological advances in this field, applications in the manufacturing sector, emerging concerns, and future research opportunities. The paper will add to the overall knowledge about how AI-based PdM is among the most important efficiency, reliability and sustainability drivers of the Industry 4.0 by analysing how it influences the existing maintenance practices.

2. Background of the Study

Traditionally, industrial maintenance has been promoted as a transition to corrective (reactive) maintenance only done when it fails, not as a time or usage-based preventive maintenance. These efforts to avert failures serve the purpose of reducing unwanted failures but at the cost of unnecessary maintenance and increased costs and wastes (Mobley, 2002). With the advent of Industrial IoT (IIoT), advanced sensors and large data platforms, predictive maintenance has become a better approach. Within AI, vibrations, temperatures, acoustics and streams of working information are processed in real-time and extracted features are used to make predictions concerning the health of equipment (Lee et al., 2018). In this sense, PdM contributes to the active decision-making that would be consistent with Industry 4.0 objectives (efficiency, resilience, and sustainability).

3. Justification

The rationale behind why AI-enhanced predictive maintenance is occurring is that AI is changing the competitive environment of industries. According to McKinsey (2018), as early as in the year 2040, predictive maintenance will be capable of halving downtime and will also enable machines to live till at least 2040. Production failures and maintenance expenses are also significant threats as the number of industries with a digitally connected property increases. It is also impossible to ignore the fact that the newest factories do not require more AI models predictive and more scalable than a human (Carvalho et al., 2019). There is also a chance that PdM passes the compatibility test with sustainability programs since it produces less waste, consumes fewer resources and less energy. Therefore, the studies carried out in this field are imperative to both economic and environmental performance.

4. Objectives of the Study

- To carry out a survey on the use of AI to predictive maintenance on smart factory.
- To study AI methods, such as ML, deep learning and reinforcement learning, in PdM.
- To determine actual case studies and their effectiveness and viability.
- To define constraints and obstacles of the AI-based PdM use.
- To suggest the future directions of strong, explainable and scalable PdM systems.

5. Literature Review

One of the disruptive components in predictive maintenance (PdM) is the emergence of artificial intelligence (AI), which is a change in how machines monitor, diagnose and forecast potential equipment failures within industries. The upkeep of the property will become easy and effective with the help of the AI, will reduce the unanticipated downtime and will increase the property prices, as the mistakes will be identified automatically and will be predicted (Zonta et al., 2020). The early versions of PdM used the typical machine learning (ML) models of support vectors (SVM), random forests, and k-nearest neighbours to a great extent. The mentioned algorithms came in quite handy to determine the existing abnormalities and locate a trend in sensor data, so, could be applied to the breaking of the regular working conditions (Carvalho et al., 2019). But thanks to the growth in scale and complexity of industrial data, deep learning models like long short-term memory (LSTM) networks and convolutional neural networks (CNNs) have become popular. Not only do the models encode a more intricate spatio-temporal relationship on the time-series signals, vibration signals, and other high-dimensional channels, which in turn, may enhance predictive performance, but the models can equally be executed in real-time (Zhang et al., 2019). Along with standalone models of both ML and DL, hybrid models have also been introduced to combine physics based models and AI methods. Positive features of such type of union are that two regions are connected and, thus, the power of physical laws, processes of the system, and outcomes informed by information, which have much greater chances to be reasonable, is obtained (Lei et al., 2018). In fact, the applications of such methodological traditions might be traced in other contexts: in the automobile industry to predict the malfunction of an engine, in the aerospace sector to optimize the operation of turbine engines, or in the power industry to guarantee a safe operation of wind turbines. As these field cases show, AI-based PdM systems may provide cost, safety and sustainability benefits.

Developments also continue to occur there and there are still a few problems that prevent implementation on a large scale. The model cannot be generalized as easily because the data are not homogenous, and the sensor form is also not homogenous. One difficulty with model training is that there is a data imbalance in that a failure event is not frequently experienced compared to standard operating conditions. In addition to that, explainability is a high-stakes issue because not every AI black-box model is transparent, and not every black-box model can be relied upon and confirmed by engineers. Finally, the almost full exploitation of industry systems in relation to the network, would pose a threat to cybersecurity of PdM systems, which would put the integrity and safety of information at risk (Zonta et al., 2020). Standardization, interpretable AI, and system design safety will be the keys to the further advancement of AI-enabled predictive maintenance.

6. Material and Methodology

Research Design: In this paper, the systematic literature review (SLR) type of research design is applied to critically review the implications of artificial intelligence (AI) in predictive maintenance (PdM) within the framework of smart manufacturing and Industry 4.0. The review procedure has been developed to be stringent, open, and repeatable such that the research can be replicated by other researchers.

Data Collection: The literature related to the topic has been collected since 2010 up to 2023 in reference to the theoretical progress and application of AI in predictive maintenance. Other possible sources of data were also peer-reviewed journal articles, and conference proceedings, and book chapters. As a result of a preliminary search, more than 150 studies were found, and after a screening and an eligibility test, 72 high-quality articles are selected to be analysed in greater detail.

Algorithms / Tools / Instruments: The reviewed research studies used a very wide variety of AI methods and involved:

- Decision Trees, Random Forests and Support Vector machines (SVMs).
- Deep Learning (DL) models with the Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs).
- Hybrid AI models, i.e. the fusion of ML/DL and optimization, digital twins, or IoT-based analytics.

The use of other tools such as Python libraries (Scikit-learn, TensorFlow, PyTorch) and industrial platforms to simulate smart manufacturing were also widely supported in the studies.

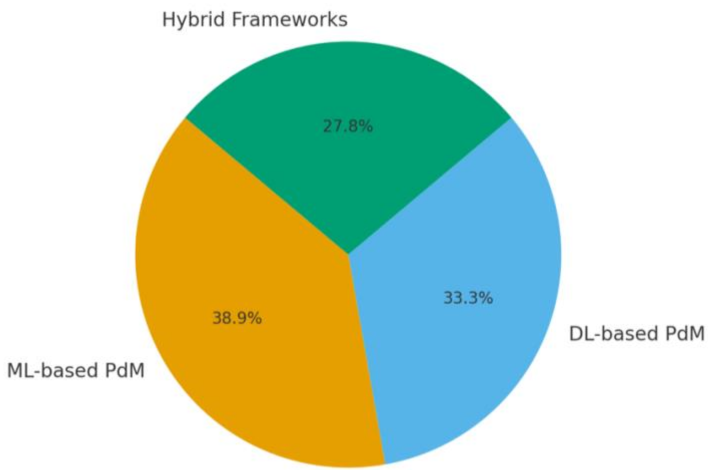

Figure 1: Distribution of Reviewed Studies by AI Approach in Predictive Maintenance

Procedure: The following steps were followed in the methodology:

1. Database Search: Four scholarly databases IEEE Xplore, Springer Link, Scopus and ScienceDirect were searched.
2. Keyword Strategy: The searches were performed using the following Boolean combinations of terms; Predictive Maintenance AND Artificial Intelligence, Smart Manufacturing, and Industry 4.0.
3. Abstracts, keywords, titles Filtration and screening of irrelevant or duplicate articles.
4. Inclusion criteria: Peer-reviewed studies only that used/requested AI-based PdM solutions were included.
5. Data Extraction: Significant information was found based on the applied AI approach, the field of application (manufacturing, energy, transportation) and restriction mentioned.

6. Categorization: To ease the comparison between the strengths and weaknesses of these studies, the studies were grouped into subgroups i.e. ML-based PdM, DL-based PdM and Hybrid frameworks.

Table 1: Algorithms, Tools, and Instruments Used in AI-based PdM Research

Category	Examples
Machine Learning Models	Decision Trees, Random Forests, Support Vector Machines (SVMs)
Deep Learning Models	Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs)
Hybrid Models	Fusion of ML/DL with Optimization, Digital Twins, IoT-based Analytics
Tools / Platforms	Python libraries (Scikit-learn, TensorFlow, PyTorch), Industrial Platforms

Statistical / validation Methods: To provide reliability the studies were compared on the basis of reported metrics of validation such as:

- Prediction Accuracy and F1-score (of model performance).
- Mean Time to Failure (MTTF) and Remaining Useful Life (RUL)-accuracy of prediction.
- Live scaling and performance of application.
- Resistance to contaminated or unclean industrial information.

7. Results and Discussion

The review comes to the conclusion PdM by use of AI saves significant sum of money and enhances the reliability.

Table 2: Key Findings of AI Models in Predictive Maintenance

Approach	Key Findings
Machine Learning Models	Effective for anomaly detection and feature learning
Deep Learning Models	Excellent at processing real-time sensor data (e.g., LSTM, CNN)
Hybrid Models	Improve interpretability by combining domain knowledge with AI
Case Studies	Reported cost savings in automotive warranties and improved scheduling for wind turbine maintenance

Figure 2: Reported Validation Metrics in AI-based Predictive Maintenance Studies

- ML models that can be used to identify anomalies and learning features.
- DL models (LSTM, CNN) perform well when processing sensor data in real time.

- Hybrid models integrate the knowledge of the domain with AI to enhance interpretability.
- Case study PdM AI-based saved car industry to warranties, and helped to arrange the maintenance of wind turbines much more relaxed, said.
- No indication of failures, old fashioned integration, and readability issues.

8. Limitations of the Study

The disadvantage of this review is that academic literature but not proprietary information of the industry was used. Additionally, PdM is run on a very large scale with very high confidence, which restricts the opportunity of proving the evidence of the large-scale applicability (Zonta et al., 2020). It also relies too heavily on labelled data, especially when there are rare failures.

9. Future Scope

The further research should be aimed at:

- Federated learning across industries with no loss of information privacy.
- Trying to be transparent in decision-making by using Explainable AI (XAI).
- Authentic integration with edge computing and blockchain of secure, real-time PdM.
- Industry 5.0 alignment, collaboration with AI and sustainability.
- It will made PdM resistive, the product can be produced and can stand when the real manufacturing is being performed (Carvalho et al., 2019).

10. Conclusion

One of the changes brought about by AI to the world of intelligent manufacturing is predictive maintenance, where equipment data and real-time information about equipment health can be delivered. PdM becomes more efficient, less expensive, and more sustainable with the implementation of ML, DL, and hybrid solutions. Scalability, interpretability and standardization issues will not go away but there is a chance to enhance PdM integration with new digital innovation technologies, such as, digital twins, federated learning and blockchain. As the world of research evolves, intelligent resilience and adaptability factories will be based on AI-based PdM.

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