AI in Predictive Maintenance for Industry 4.0 - an overview.

Master's thesis

Industrial Maintenance Management and Engineering

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Abstract: The advent of Industry 4.0 has ushered in a new era of smart manufacturing. Artificial Intelligence (AI), and more specifically, machine learning, stands at the forefront of this transformation, offering unprecedented opportunities for predictive maintenance. This article delves into the crucial role of AI, particularly machine learning algorithms, in the context of Industry 4.0, emphasizing their significance in predictive maintenance applications. The article explores how machine learning models used in predictive maintenance can be divided according to their role. Predictive maintenance not only reduces downtime, but also improves overall operational efficiency. The integration of artificial intelligence and machine learning technologies promotes the shift from reactive to proactive maintenance strategies, thus improving resource use and extending the life of industrial assets. However, despite promising progress, the application of machine learning in predictive maintenance is not without challenges. The article discusses key obstacles such as data quality and accessibility, problems in choosing machine learning models, and the need to adapt to dynamic industrial environments. It discusses the importance of creating a robust data infrastructure and developing transparent models to build trust in AI-based predictive maintenance systems.

Key-Words: Smart Maintenance, Artificial Intelligence (AI), Machine Learning (ML), Predictive Maintenance, fault prediction, Condition Monitoring, Industry 4.0, Internet of Things (IoT), Cyber-Physical System (CPS).

Contents

1. Introduction

The signs of progress in the modern era are unmistakable with the advent of what is known as 'Artificial Intelligence.' This revolutionary technology has not only reshaped our understanding and boundaries of human capabilities but has also fostered the development and innovation of more efficient and contemporary methods across various fields, including industrial maintenance, ushering in a new era of predictive maintenance and conditions monitoring.

This shift has led to: "The Fourth Industrial Revolution", also called industrial 4.0 [1], It represents a way towards the use of smart technology, data exchange, and automation in manufacturing and other industrial sectors. Where there is communication between various systems in real time, increasing efficiency and productivity and creating more flexible and adaptive production systems. The goal is to reach the stage of immediate response to various changes in real time, and thus improve the quality of decisions and production capabilities and achieve what is known as: the 'smart factory'[2]. This revolution aims to transform traditional industries by leveraging advanced technologies to enhance connectivity, automation, and data-driven decision-making. This type of advanced industry requires the intervention of advanced technologies, including: the Internet of Things (IoT), artificial intelligence (AI) and cyber-physical systems (CPS)[2], to create smart and interconnected systems in manufacturing and other industries.

The Internet of Things (IoT) is defined as an ecosystem in which the objects and equipment inserted in it are equipped with sensors and other digital devices. This enables them to gather and exchange information with each other in a networked system [3]. This feature allows for effective and accurate monitoring of various systems and mechanisms, and also allows for the possibility of integrating it with other advanced technologies to achieve functional integration. Internet of Things (IoT) and Cyber-Physical System (CPS) technologies play roles in this context, introducing cognitive automation and consequently implementing the concept of intelligent production, leading to smart products and services.

Simultaneously, the IoT allows real-time transmission of this information about the conditions of the systems captured by different monitoring devices. This development offers an excellent opportunity to use condition monitoring data intelligently within predictive maintenance, combining the ability to collect data with an effective and integrated analysis of it [3].

Predictive maintenance (PdM) uses artificial intelligence algorithms to determine when maintenance actions are necessary. It relies on continuous monitoring data of the machine, allowing maintenance to be performed only when it is needed. The monitoring process is carried out by special sensors in real time [3]. However, analyzing the huge amount of sensor data is usually not possible. Therefore, machine learning (ML) can be used to analyze such data. In this regard, it is necessary to highlight a set of pivotal questions, which are as follows: What ML methods are being used for PdM? Is it really useful? What are the challenges we face?

The remainder of this article is organized as follows: Section 2 discusses the research question, Section 3 explores the integration of Artificial Intelligence in Industry 4.0. Section 4 outlines the research methodology. Subsequently, Section 5 highlights the advantages of utilizing AI in predictive maintenance, Section 6 delves into the learning models commonly employed, and Section 7 addresses the challenges associated with implementing AI in predictive maintenance. Finally, Section 8 a conclusion.

2. Research questions

The process of identifying articles directly affects the quality of the analysis due to the availability of huge amounts of articles on scientific research sites. Therefore, the selection process creates a challenge and an opportunity for excellence. Therefore, distraction and focus of search operations must be avoided by setting systematic questions that allow directing the research process. Therefore, we determined questions to be applied to each article to determine its suitability to the research topic, which are as follows:

1- What are the benefits of applying AI in predictive maintenance?

2 - What machine learning models are typically used?

3 - What are the challenges of applying artificial intelligence in predictive maintenance

3. Innovating of Industry 4.0 with Artificial intelligence

In the dynamic landscape of Industry 4.0, industrial has become closely intertwined with the integration of physical and digital systems [4], marked by the integration of computerization and the Internet of Things (IoT) and many advanced technologies across various industries. The copious data harnessed from these systems stands as a linchpin for elevating operational efficiency, strategic decision-making, to reducing maintenance costs and other benefits [5], [6].

This integration allows for the seamless collection of extensive data from diverse equipment located throughout factory sectors, encompassing information about processes, events, and alarms along industrial production lines [1]. Comprehensive analysis of this data not only yields insights but unlocks a range of benefits: From diminishing maintenance costs and minimizing machine faults to reducing spare parts inventory and enhancing operator safety, the advantages contribute to an overall boost in profitability[5], [7].

In this advanced technical landscape, it is necessary to create a new type of capabilities that allow coexistence with this technologically advanced environment, which has been embodied in artificial intelligence. As a result, the adoption of artificial intelligence is seen as pivotal to effective operation and maintenance policies, and taking advantage of big data [4] and diverse sources of information to bridge the gap between technology, organization and operations.

This has allowed the emergence of many advanced systems including: Smart Manufacturing , Digital Twins, Cobots, Cybersecurity and other advanced systems [1]. Thus, we see some aspects of its importance in addressing the weaknesses of traditional maintenance in adapting to advanced technologies.

In conclusion, it can be said that: "AI integration is essential to harness the full potential of Maintenance in the context of Industry 4.0».

4. Research Methodology

4.1. Step 1: Search engines selection

In order to learn about the last developments in the field of applying artificial intelligence in predictive maintenance, I systematically analyzed a group of free articles available on the SNDL platform.

The search process was mainly focused on a group of scientific search engines, which are as follows: Google Scholar, IEEE, ScienceDirect and other scientific search engines. Google Scholar was the starting point in the search process because it contains a wide number of free articles. Although there are some articles that do not focus on application of AI in predictive maintenance. The purpose of this process is to obtain the largest possible number of articles surrounding the idea of the article and then perform many filters to take a general picture of the current state of application of artificial intelligence in the field of industry in general and in predictive maintenance in particular.

4.2. Step 2: Article selection

To facilitate the search process and save time, the three most famous search engines that contain the largest number of free articles were chosen to avoid repeating the same articles as much as possible in other engines, which are as follows: Google Scholar, IEEE and Science Direct. The following search string was applied: “industry 4.0” or “smart manufacturing” and “internet of things” and “predict maintenance” and “Artificial Intelligence” or “Machine learning”, on 11/17/2023 with the application Time filter from 2018-2023 on the previously mentioned search engines, and the initial result was that 286 articles appeared in Google Scholar, 7 in IEEE, and 668 in ScienceDirect, thus obtaining 1102 articles.

Next, it is filtered through a series of filtration as shown in Table A. In the end, 11 articles remain on which the study focuses.

Stages	Description
Stages 1	Filter looking for period of 6 years, 2018-2023 Google Scholar:286. IEEE:7. Science direct:668
Stages 2	Remove books, technical reports, Conferences and theses; Google Scholar: 71. IEEE:7. Science direct:121
Stages 3	Remove all publications that do not use the search terms "industry 4.0", "smart manufacturing", "internet of things", "predict maintenance", "Artificial Intelligence" and "Machine learning" in the title, abstract or keywords. Google Scholar:71. IEEE: -1=7. Science direct: -59=62
Stages 4	Remove all duplicate and publications that do not address prediction or monitoring applied to Industry 4.0, smart manufacturing, or IoT as a model, method, or architecture. As result: obtain 11 articles

Table A: The set of filters applied in the search process

4.3. Step 3: Scorecard

The objective of the scorecard is to assess the degree to which research articles have influenced the formulation of the present article, thus the assessment criteria were centered around the alignment of each chosen article with the research inquiries. Allocation of a point to each article corresponds to its relevance to a specific research question. This approach was embraced by Jovani et al [4].The results of the operation are shown in Table B and are expressed in Figure 1 in a more simple and clear way.

Q1: What are the benefits of applying AI in predictive maintenance?

Q2: What machine learning models are typically used?

Q3: What are the challenges of applying AI in predictive maintenance?

No.	Article title	Year	Q1	Q2	Q3
1	Application of Predictive Maintenance Concepts Using Artificial Intelligence Tool	2018	1	1	1
2	Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status and challenges	2020	1	1	1
3	Generation of Complex Data for AI-based Predictive Maintenance Research with a Physical Factory Model	2019	1	1	1
4	Maintenance 4.0 Systems Architecture: Challenges and Opportunities	2022	1	1	1
5	A systematic literature review of machine learning methods applied to predictive maintenance	2019	0	1	1
6	Systematic Literature Review on Industry Revolution 4.0 to Predict Maintenance and Life Time of Machines in Manufacturing Industry	2023	1	1	0
7	A Review of Artificial Intelligence Methods for Condition Monitoring and Fault Diagnosis of Rolling Element Bearings for Induction Motor	2020	1	1	1
8	Predictive maintenance in the industry 4.0: A systematic literature review	2020	0	1	1
9	Machine Learning in Predictive Maintenance towards Sustainable Smart Manufacturing in Industry 4.0	2020	1	1	1
10	Modeling System Based on Machine Learning Approaches for Predictive Maintenance Applications,	2020	1	1	0
11	Use Case of Artificial Intelligence in Machine Learning Manufacturing 4.0	2019	0	1	0

Table B: Scorecard

The results of the research methodology that was adopted were expressed in a simplified way in Figure 1, which shows a diagram that expresses the extent to which the selected articles relate to our article. Three distinct colors are used: blue for the first research question: Q1, green for the second research question: Q2, and red for the third research question: Q3. In addition, the scores corresponding to each question are also displayed in the vertical axis. As for the horizontal axis, it represents the articles that were identified during the search process.

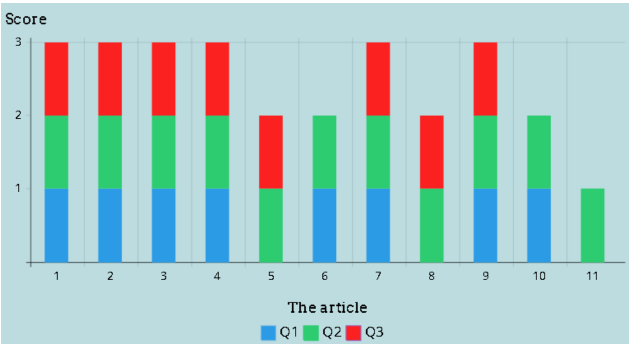

Figure 1: Scorecard representation

5. What are the benefits of applying AI in predictive maintenance

Predictive maintenance, empowered by Artificial Intelligence (AI) tools, particularly Machine Learning (ML), has emerged as a transformation force in industrial settings. This approach offers multifaceted benefits, as outlined in various references[8],[6].

One key advantage is the potential for improving system availability while concurrently reducing maintenance costs. Machine Learning facilitates the intelligent analysis of condition monitoring data, allowing for a more precise evaluation of effectiveness through metrics such as cost reduction and time spent on maintenance tasks [4],[9]. The application of ML in predictive maintenance is not confined to specific equipment or industries; rather, it spans diverse areas, demonstrating its versatility.

The integration of ML algorithms in predictive maintenance extends to fault detection and diagnosis (FDD) and condition monitoring (CM) [9]. This is particularly crucial for early diagnosis, preventing severe damage to industrial infrastructure. Continuous monitoring of valuable equipment enhances safety, reliability, and availability while decreasing maintenance costs [9].

The efficacy of ML in predictive maintenance is further accentuated by advancements in hardware, cloud-based solutions, and state-of-the-art algorithms. The seamless integration of ML into industrial processes and system dynamics not only enhances productivity but also serves as a decision support tool, particularly in condition-based maintenance and health monitoring [10].

ML applications yield a multitude of advantages, ranging from maintenance cost reduction to increased operator safety and overall profit. The references [3],[5],[11] reinforce the profound impact of ML in reducing repair stops, machine faults, and spare-part usage, ultimately contributing to increased production efficiency.

As result, the amalgamation of AI, specifically ML, into predictive maintenance strategies brings about a paradigm shift in industrial maintenance practices. The cited references collectively affirm the diverse advantages, including cost reduction, increased safety, and enhanced overall productivity, positioning AI as a cornerstone in the evolution of maintenance methodologies.

6. What machine learning models are typically used

Artificial intelligence (AI) algorithms, particularly those based on machine learning, play a pivotal role in predictive maintenance across various industries. According to what Diogo Cardoso & Luís Ferreira (2020) [3] say: “Regarding the use of Machine Learning algorithms in scientific publications, the most used is Random Forest (RF)-33%, followed by methods based on Neural Networks (NN), such as Artificial NN, "Convolution NN, Long Short-Term Memory Network (LSTM) and Deep Learning-27%, Support Vector Machine (SVM)-25% and k-means-13%. There was also a greater tendency to use vibration signals». To effectively address the multifaceted challenges of maintaining complex systems and equipment, these algorithms are categorized into distinct sections based on their roles. The key divisions include fault prediction and detection, data fusion, time-series prediction, fault detection and diagnosis, predicting the remaining useful life (RUL), and classifying algorithmic failures. This is as shown in Figure 2.

Fault Prediction and Detection: In this category, AI algorithms focus on predicting potential errors in machines or systems before they occur. Machine learning models can analyze historical data to identify patterns or anomalies that may indicate impending failure. In context, many authors have used several types of Neural Networks (NN) especially Recurrent Neural Networks (RNN) [4] and Convolutional Neural Network (CNN), a class of deep learning algorithms, which was proposed by (Pan et al.[12], 2017; Huuhtanen & Jung, 2018 [13]). Another ML used is Autoregressive Moving Average (ARMA) . Rivas et al.[14] also adopted Long Short-Term Memory (LSTM) for failure prediction.

Data Fusion: involves combining information from multiple sources to enhance the accuracy and reliability of predictive maintenance models. AI algorithms can integrate data from various sensors, equipment, and systems to provide a comprehensive and holistic view of the operational status. This aids in making more informed decisions and improving the overall effectiveness of maintenance strategies. Huang et al.[15] confirmed this idea by used algorithms based on neural networks, Back-Propagation Neural Network (BPNN), Radial Basis Function Neural Network (RBFNN), Elman Neural Network (ENN), Probabilistic Neural Network (PNN), Fuzzy Neural Network (FNN) and Wavelet Neural Network (WNN). Then we can use this combined data to perform fault prediction and detection.

Time-series prediction is crucial for forecasting equipment behaviour over time. AI models, particularly those based on k-Nearest Neighbor (kNN) or Backpropagation Feed-forward Neural Network (FFNN), Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and Naïve Bayesian (NB) can analyze time-stamped data to make predictions about future states, this was confirmed by Schmidt et al.[16] through his research. From another angle, this is valuable for anticipating trends, identifying performance degradation, and scheduling maintenance activities accordingly.

Fault Detection and Diagnosis: Unlike fault prediction, fault detection involves real-time monitoring to identify and flag anomalies or malfunctions as soon as they occur. AI algorithms in this category are designed to swiftly detect deviations from normal operating conditions and trigger alerts for immediate attention. Further, diagnostic capabilities help in pinpointing the root causes of faults, facilitating a targeted and efficient maintenance response. The most popular ML models in this category Bayesian Network (BN)[9],[17], Artificial neural network (ANN)[18],[19] and (SVM) [19]. In the same context, a special BN, called Dynamics Bayesian Network (DBN), is proposed by Ansari et al.[18]. Other models have been proposed by Xia et al., 2017.[20] called Stacked Denoising Autoencoder (SDA).

Predicting Remaining Useful Life (RUL): Predicting the remaining useful life of equipment or components is essential for optimizing maintenance schedules. Machine learning models analyze historical performance data to estimate how much life is left in a system. This information aids in planning maintenance activities, ensuring that components are replaced or serviced just in time to prevent failures. Due to this extreme importance, many authors and researchers have paid attention to this field, including Zheming Tong et al., 2021[21], whose proposed a hybrid machine learning model for lithium-ion batteries.The scientific community also presented many other models, most notably: Auto-regressive Integrated Moving Average (ARIMA)[22], Network of Extreme Learning Machines (N-ELM) (Yang & Zhang, 2016) [23]. and Deep Belief Network (DBN) (Deutsch & He, 2018) [23].In the same context, Calabrese et al.[24]proposed three models based on tree-based algorithms: Gradient Boosting Machine (GBM), the Distributed Random Forest (DRF), and Extreme Gradient Boosting (XGBoost) models. The GBM provided the best result to classify machines with 30 days of less of RUL.

Classifying Algorithmic Failures: In cases where AI algorithms themselves might encounter issues or failures, classification algorithms can be employed to identify and categorize these algorithmic failures. This ensures that the reliability and performance of the predictive maintenance system are continuously monitored and improved. In this classification, most authors used the support vector machine (SVM) [22],[25],[26],[25],[27].

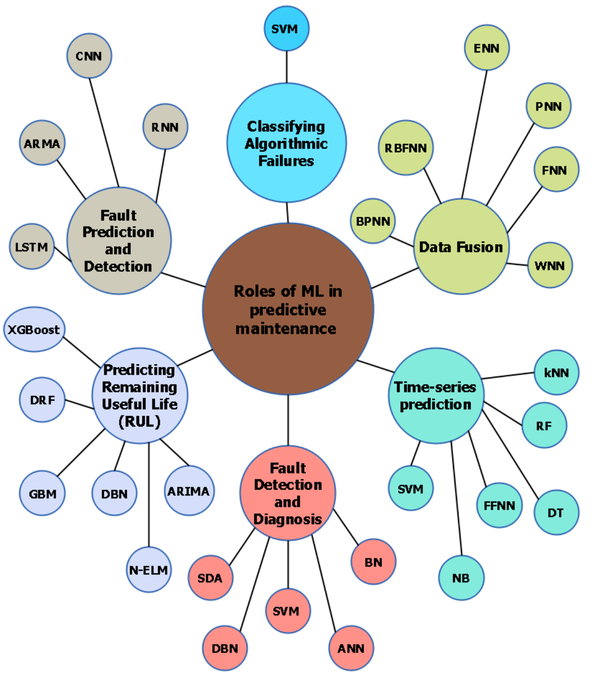

Figure 2: Classification of Machine Learning model for predictive maintenance

7. What are the challenges of applying AI in predictive maintenance

Applying machine learning in predictive maintenance comes with its set of challenges, from intricacies in data collection/quality to the dynamic nature of operating environments, the selection of appropriate features, the demand for real-time monitoring, the absence of a universal model for diverse scenarios, the nuances of batch learning and the necessity of context-aware ML information, this reflects the complexities inherent in real-world industrial environments.

Data collection/quality: Gathering pertinent data for training machine learning models is frequently a substantial challenge due to its collection from various sources and systems [28],[25],[29],[30],[31],[32],[33]. In predictive maintenance, obtaining comprehensive datasets that represent the diversity of operating conditions and failure modes can be difficult. This is due to a set of challenges that include of the lack of labelled data [34] and training data [35], the need for transfer learning [28], as well as the necessity of explainable decision support [28]. Also, the challenge of quickly exploiting important information that is extracted from the Big Data coming from the sensors [9]. Which was classified by Rodríguez-Mazahua et al. (2016) [36] to six Big Data challenges. Additionally, ensuring data quality, consistency, and reliability is crucial for building accurate models. We distinguish two types of challenges that address this idea: Imbalanced data [1],[37] and heterogeneous data [38], [39].

Dynamic Operating Environments: Industrial systems operate in dynamic environments with varying conditions. Adapting machine learning models to account for changes in operating parameters, environmental factors such as noise, is a big challenge [1],[35]. For that, models need to be robust enough to handle disturbances resulting from measurements to ensure accurate predictions.

Feature Selection for ML: Choosing the right set of features that best represent the system's behaviour is crucial for model performance. The challenge lies in identifying the most relevant features that capture the early signs of potential failures. Feature engineering and selection require domain expertise and continuous refinement as the system evolves. A less correct choice may lead to many errors in predictive maintenance [3].

Real-time Monitoring: Many predictive maintenance applications demand real-time monitoring to detect anomalies and faults promptly [35],[40]. To achieve that, efficient algorithms and infrastructure are needed to process large amounts of data quickly and make timely predictions.

Unavailability of a universal machine learning model: There is no one-size-fits-all model for predictive maintenance. Different industrial systems, even within the same industry, may have unique characteristics and failure modes. Developing a universal model that performs well across diverse scenarios is challenging. Therefore, it is necessary to choose the ML algorithm that best suits a particular scenario [22].

Batch Learning Challenge: Continuous learning and adaptation are essential to accommodate changes in the system behaviour over time. Therefore, the inability of models to train immediately when obtaining new data is considered one of the biggest problems, and this is known as the Batch Learning Challenge [3].

The necessity of context-aware ML information: Context-awareness allows machine learning models to account for specific environmental factors, operational nuances, and historical patterns that may influence the performance and potential failures of equipment [37]. Failure to incorporate context-aware information can result in models that are too generic or fail to adapt to the intricacies of particular industrial processes, limiting their accuracy and effectiveness.

There exist numerous models of machine learning, extending far beyond the 28 models previously discussed, encompassing hundreds of variations. Similarly, the roles of artificial intelligence on predictive maintenance extends beyond the six roles outlined, focusing on the most crucial aspects. Furthermore, during the research process, I relied only on three search engines only: Google Scholar, IEEE, and ScienceDirect.

8. Conclusion

This article can be considered a reference for the authors as it sheds light on the latest developments in the application of machine learning in the field of predictive maintenance, specifically with regard to the benefits of its application, including reducing maintenance costs and time spent on maintenance tasks and extends to fault detection and diagnosis (FDD) and condition monitoring (CM). This allows for enhanced safety, reliability, and availability while decreasing maintenance costs.

The article also addressed one of the key aspects of successful implementation of machine learning in predictive maintenance is understanding the role of different types of models in the process. Classifying machine learning models based on their specific functions is crucial to designing a comprehensive and effective predictive maintenance system. Starting from Fault Prediction and Detection, Data Fusion, Time-series prediction, Fault Detection and Diagnosis, Predicting Remaining Useful Life (RUL), Classifying Algorithmic Failures. However, amid the promising advantages, it is important to acknowledge the challenges associated with implementing machine learning in predictive maintenance. This is what was discussed in the end, as it was divided into several classes: Data collection and Data quality, Dynamic Operating Environments, Feature Selection for ML, Real-time Monitoring, Unavailability of a universal machine learning model, Batch Learning Challenge and the necessity of context-aware ML information.

In overcoming these challenges, organizations can unlock the full potential of machine learning in predictive maintenance, paving the way for a more sustainable and optimized industrial landscape. As technology continues to advance, leveraging machine learning in maintenance strategies will become increasingly indispensable for businesses seeking a competitive edge in today's dynamic and demanding market environment. In essence, the convergence of data-driven insights and proactive maintenance approaches not only enhances operational efficiency but also contributes to a safer, more reliable, and cost-effective industrial ecosystem.

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