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Predictive Maintenance in Industry 4.0 - Adopting Machine Learning to Overcome Challenges and Open Issues

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Abstract

Predictive Maintenance is one of emerging concepts arisen with industry 4.0, playing a vital role in production systems and sustainable manufacturing by introducing maintenance with machine learning. Data gathered from production have increased significantly because of sensing technologies. Even though there are challenges related to organization, finances, and even repair and data source, Maintenance 4.0 has emerged as a strong point for organizations using it. Indeed, it minimizes costs and downtime associated with machine, increasing the life span of machine, and improves quality of production. Industry 4.0 has brought a significant change in manufacturing, forcing industries for adopting innovative approaches to streamline decision-making. Predictive Maintenance is an important component of this revolution, playing a central role by leveraging machine learning among other approaches for this transformation to optimize maintenance schedules, predict equipment failures, and improve operational efficiency. This study is based on the process of "Systematic Literature Review (SLR)" of 216 peer-reviewed papers published from 2019 to 2024, analyzing machine learning used for predictive maintenance in several industries, such as, machinery, manufacturing, smart systems and energy. Unlike previous literatures examining ML methods, this review offers structured taxonomy of approaches for predictive maintenance, highlighting their prevalence and domain-centric uses in industries based on safety.

Keywords – predictive maintenance, machine learning, industry 4.0, decision-making, smart systems

1. Introduction

In the existing economic context with widely demanding and globalized markets, industries are known to improve the efficiency and performance of production lines to meet customer needs and competitive edge. Data, connectivity, new devices, customization, inventory reduction, and controlled production have brought Industry 4.0 (Rüßmann et al, 2015). It suggests the need for applying automation approaches for integrating new technologies which will improve productivity (Jasiulewicz-Kaczmarek and Gola, 2019). The integration of "artificial intelligence (AI)", big data, "Internet of Things (IoT)", and "cyber-physical systems (CPS)" play a vital role in bringing cognitive automation and adopting the concept of smart production, resulting in smart services and products. ith this innovative approach, companies can address challenges in dynamic world. This way, organizations can improve the life of their equipment when it comes to reduce energy costs and consumption and unplanned downtime with predictive maintenance (Zhu et al, 2019). Predictive maintenance has been promising, offering solutions for the rest of equipment lifetime by predicting data collected by several equipment sensors (Tiddens et al, 2023). It has reached a lot of importance for industries with rising interactions across various activities in a lot of ecosystems related to manufacturing. Figure 1 illustrates global trend for the use of smart maintenance till 2030. Overall, approaches for contemporary maintenance vary as per the use of several learning models and different issues faced by equipment and machines. However, prognosis and fault diagnosis in predictive maintenance should be very clear and accurate (Blancke, 2020). Prediction, interpretation, and detection in equipment are based on data collected from the equipment sensors in order to build smart manufacturing solution (Tiddens et al, 2023). It is worth having slight idea of challenges and benefits when it comes to apply predictive maintenance on data source, equipment, organizational, and financial side. Indeed, predictive maintenance includes data mining for designing ML models predicting the state of equipment health and knowledge. This way, predictive maintenance includes several approaches like "Remaining Useful Life (RUL)", "Condition-Based Maintenance (CBM)", and "Prognosis and Health Management (PHM)".

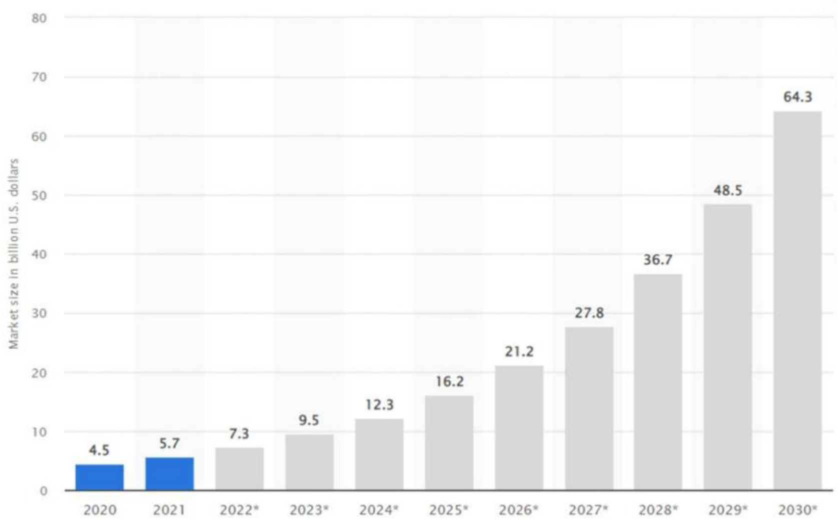

Figure 1 – Worldwide Market Size of Predictive Maintenance (2020-2030)
Source – Predictive Maintenance Market Size (2023)

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2. Literature Review

This chapter provides in-depth insights to the concepts introduced in past studies and also covered in this study – machine learning and predictive maintenance.

2.1. Predictive Maintenance:

There has been a significant evolution of industrial maintenance over the years, from interventions to smart approaches to optimize operational efficiency. In corrective maintenance, system failure leads to repair process. It was originally a dominant strategy. Though easy to implement, this approach extends repair costs, downtime, and unplanned disturbance. Industries have adopted preventive maintenance to reduce these issues, following a plan for scheduled maintenance on the basis of usage limits and specific time intervals. Even though preventive maintenance can reduce sudden failures, it can also lead to unwanted servicing, increasing operation costs without having to improve efficiency (Zhu et al, 2019). This challenge is especially important in modern industries, where downtime of the machinery can result in 60% of operation costs, making it vital for strategies to be more accurate and cost-effective (Zonta et al, 2020). It has improved predictive maintenance. It is a modern approach using past data analysis and real-time monitoring to anticipate failures before they take place. When performing maintenance actions only when needed, predictive maintenance reduces downtime, extends the lifespan of assets and optimizes use of resources. Condition monitoring is well-known to be a key enabler for predictive maintenance, which covers collection of real-time data into the sensors like temperature, vibration, electrical signals, and pressure. Then, this data is processed with advanced analytics to predict possible failures and detect anomalies. However, effective condition monitoring relies on availability of representative, high-quality data across all conditions (Wang et al, 2017). There are basically three key categories of predictive maintenance approaches – (1) Knowledge models integrating heuristics, expert knowledge, and fuzzy logic to estimate failure conditions; (2) Physical models depending on engineering principles and equations to define degradation of the system; and (3) Data-based models employing statistical approaches, Artificial Intelligence (AI) and, pattern detection to analyze real-time and past data to predict failures (Meriem et al, 2023). Deep learning, fog computing, and IoT monitoring are integrated by recent advancements to improve scalability and predictive accuracy (Teoh et al, 2021). Data-based Machine Learning (ML) models have been prominent because they can handle large sensor data and complex patterns. Benchmark datasets which are available in public have played a vital role in evaluating and developing such techniques. The "NASA CMAPSS" is the most widely used dataset which simulates degradation of engine in turbofans of aircrafts and "PHM Society Challenge" offers realistic scenarios for industrial failure (Jakobsson et al, 2022; Tominaga et al, 2023). These datasets are well regarded to compare predictive maintenance (PdM) models to establish common standards for evaluation across industrial and academic studies.

2.2. Machine Learning

A subfield of AI, ML enables automatic learning and improvement of systems from data by detecting relationships and patterns (Burkov, 2019; Mitchell, 1999). Usually, it is classified into four models (Russell and Norvig, 2010) –

- Supervised learning consists of training model on datasets which have been labelled, helping to learn relationship between outputs known and input features.
- Semi-supervised learning uses both unlabeled and labelled data to improve learning.
- Unsupervised learning is used to track unlabeled data to detect hidden structures and patterns without specified categories.
- Reinforcement learning depends upon the agent which interacts with environment to improve increasing rewards through trial and error.

This study focuses majorly on supervised machine learning technique as it is very effective for predictive maintenance. On the other hand, unsupervised machine learning struggles with vague patterns and reinforcement learning needs a lot of trial and error. Supervised learning offers accurate and structured predictions on the basis of past failure data (Berry et al, 2020). It helps improve predictive accuracy, analyzes complex patterns of data, and identifies trends related to degradation (Guidotti et al, 2023a). Supervised machine learning provides automated solutions, making it valuable in environments related to Industry 4.0 and can process vast datasets effectively in comparison to traditional methods (Ge et al, 2017). Supervised machine learning helps in anomaly detection, failure prediction, and in diagnosing faults. By leveraging data which is historical labelled, models can identify early signs of warning related to degrading equipment, reducing unwanted downtime and timely intervention (Guidotti et al, 2023b). Usually, implementation consists of extraction of sensible features, collection of sensor data, real-time monitoring, and training of predictive models. Deep learning has been prominent because it can learn hierarchical features automatically from raw data. Remarkable performance is observed to capture complex sensor patterns with "Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Deep Neural Networks (DNNs), and Recurrent Neural Networks (RNNs)."

CNNs can analyze image sensors and vibration signals, while "Long Short-Term Memory (LSTM)" and RNNs are best suited for sequential data like reading time-series sensors (Nguyen-Da et al, 2024). In addition, "Transfer Learning (TL)" has been an important technique for deep learning. This approach improves performance and efficiency, especially in PdM uses (Coutinho & Boukerche, 2022).

2.3. Research Questions

Based on the above literature reviews, here are the research questions to explore the role of ML in predictive maintenance, PdM tools and techniques, and relevant industrial challenges –

RQ1: What are the widely used techniques in predictive maintenance?
RQ2: What are the tools used in predictive maintenance in context of industry 4.0?
RQ3: What are the industrial challenges related to predictive maintenance?

3. Research Methodology

This chapter discusses the research methodology adopted to answer the research questions. It focuses on study design and explains the process of literature search to ensure comprehensive and in-depth review.

3.1. Study Design

This study adopts "systematic literature review (SLR)" approach which is widely used for systematic evaluation, identification, and interpretation of relevant research associated with specific area, issue, and interest (Carrera-Rivera et al, 2022). Primary goal of SLR is to perform comprehensive research to critically assess their approaches, and combine them into structural analysis, covering meta-analysis and structural analysis. For transparency, reproducibility, and consistency, a hybrid approach has been adopted, covering elements from guidelines for systematic reviews related to software engineering by Kitchenham et al (2010).

3.2. Literature Search

This study carefully examines both databases and search terms used to review literature, such as, "Artificial intelligence", "AI", "Industry 4.0", "Predictive Maintenance", "Smart Manufacturing", and "Maintenance 4.0. This study is based on peer-reviewed, high-quality articles published on databases like ACM Digital Library, IEEE Xplore, and Scopus, related to application of ML and AI in predictive maintenance, in context of Industry 4.0. These digital libraries were selected because they are ideal for IT and computing research, especially ML and AI applications in industry 4.0. They also include high-impact journal and conference proceedings in the field of manufacturing, engineering and AI.

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4. Data Analysis

4.1. Widely used Techniques in Predictive Maintenance

As the subfield of AI, machine learning (ML) has evolved from pattern identification to integrate the same and analyze data structures into models that can be understood and regenerated by users (Barja-Martinez et al, 2021). Figure 2 identifies all methods, categories, and models of ML applicable to projects related to maintenance (Nacchia et al, 2021). In addition, ML is categorized into four categories, i.e., reinforcement learning, deep learning, unsupervised learning, and supervised learning. Types of unsupervised and supervised learning are aimed to describe or predict current relationships in a dataset, which are supposed to be supervised. Dependent variables are available in supervised learning and they are not applicable in unsupervised learning. Computational approach is used by reinforcement learning from communication with the environment, which refers to evaluating how these system actors can act in their environments to improve cumulative rewards.

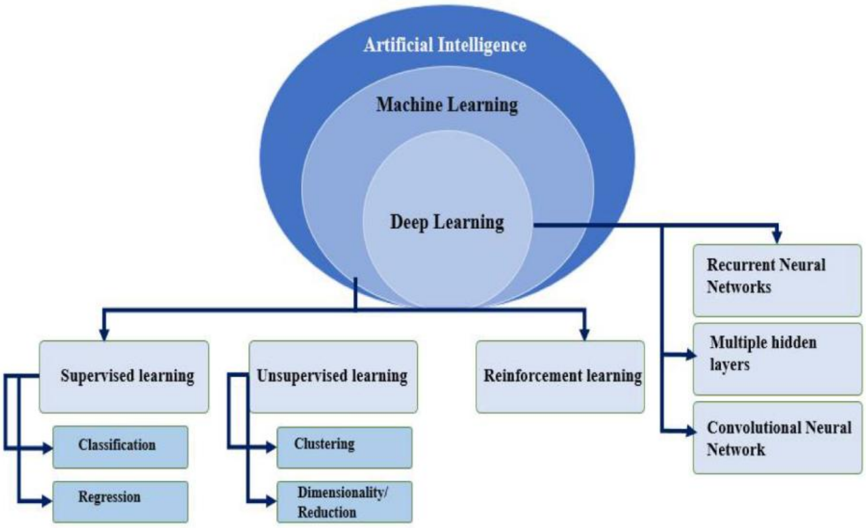

Figure 2 – A flowchart of categories of Machine Learning techniques
Source – Nacchia et al (2021)

On the other hand, deep learning relies on “artificial neural networks (ANNs)”. It is a huge group of techniques in a lot of fields, applicable to both unsupervised and supervised learning. ANNs are influenced by brain function, while the goal is to learn from unlabeled or unstructured data, with multiple layers to extract features of higher level from raw input. DL techniques can be applicable to industrial equipment manufacturing in various situations like failure prediction or fault detection.

Speaking of predictive maintenance, Keleko et al (2022) identified some of the machine learning techniques used in context of industry 4.0 –

Decision Tree

Decision Tree (DT) represents data through a tree structure using recursive partitions on the space. It is based of “divide and rule” principle. In addition, DT consists of “root” or best predictor across all subsets. The model can be used for solving regression or classification tasks that can be useful in various applications (Giannetti and Ransing, 2016; Jung et al, 2018).

Random Forest (RF)

Breiman (2001) have developed the “Random Forest (RF)” model. RFs are based on voting and combination of a range of random trees to evaluate each node individually. In addition, RF model improves decision trees, especially related to variance control and instability. In various applications, Random Forests are used for regression or classification challenges (Kim et al, 2020; Ayvaz and Alpay, 2021).

Support Vector Machine (SVM)

Vapnik (2013) has developed the (SVM) model. It deals with generalized model with hypothesis of linear function by generating optimal partition in high-dimensional feature. Optimization problems offer convex solutions in the restricted setting. In addition, SVM has been more popular for uses in handwriting and face analysis and image classification. Cakir et al (2021) and Gryllias and Antoniadis (2012) applied SVM for monitoring electronic or mechanical machine.

K-Nearest Neighbor (K-NN)

K-NN is a non-parametric classification model based on classifying new classes of samples which are highly similar (Altman, 1992). They are used more often in industrial applications for recommendation or pattern recognition problems. An improved version “WKNN” is exploited by the Jung et al (2018) for isolation and fault detection tasks of complex systems. In addition, “distance weighted k-nearest neighbors (WKNN)” are more efficient as compared to K-NN when separating the classes

In predictive maintenance, production optimization plays a vital role. PdM has been a center of attraction for a lot of organizations. There are several benefits of predictive maintenance for an organization, such as –

- Reduced time in lost performance
- Enhancing revenues
- Improved safety
- Reduced machinery costs
- Efficient maintenance personnel
- Reduced labor costs

With recent advancements, it is possible to track and measure parameters of production in real-time with modern sensors. Additionally, there is plenty of data to implement prediction techniques smoothly. By monitoring the machine, possible failures like mechanical wearing, unbalance, misalignment, faulty bearings, and cracking teeth can be forecasted and it can safely intervene with maintenance to avoid sudden breakdown in production. Machine diagnosis offers useful data related to its condition and status. A machine offers several signs which convey signals on operation conditions when processed. There are several approaches for diagnosis as per the type of information processed –

Acoustic diagnosis - Acoustic diagnosis refers to analyzing acoustic signals produced by machine to detect problems or anomalies. Because of limitations, there is lack of studies on acoustics diagnostics which have been conducted in controlled manner (Ahmed et al, 2021).

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Thermography – It is another most common technique used in predictive maintenance. This approach relies on analyzing radiation emitted by objects. This way, anomaly can be detected with the rise in temperature related to normal conditions. However, it relies on environment (humidity and temperature) and equipment cost is high (Shukla et al, 2022).
Oil Analysis – It is the predictive maintenance approach that can track operations of plants and industrial machines by tracking the oil or lubricant in equipment. However, initial costs are very high in this technique and needs specialized analysis knowledge. Additionally, oil analysis may not detect all kinds of mechanical anomalies or faults.
Visual Inspection (VI) – It is among the easiest and oldest diagnosis approaches in maintenance. It directly observes component or plant to determine the condition.
Vibration Analysis – With rotating or reciprocating components, mechanical systems vibrate due to mechanical disturbances from different sources like sound, engine, and noise. "Vibration" is the term used in "mechanical engineering", which usually refers to systems oscillating without outer forces freely. It can provide sustainable monitoring and is known for non-destructive nature without having to interfere with the processes (Goyal and Pabla, 2016).

4.2. Tools used in Predictive Maintenance

Industry 4.0 revolutionizes the way companies improve, distribute, and produce their products. It has significantly transformed the world of manufacturing and industries with intercommunication across equipment using Big Data, IoT, decision-making and intelligence systems (Li et al, 2017). This digital technology helps organizations to reach more rapidly to changes in the market, improve operational efficiency, and provide more tailored products with informed Big Data to produce products more productively and efficiently through the value chain. They provide real-time information on the status of machines, including operating speed and leakage location.
This technology helps in deploying smart industries as it reproduces data in real-time through the supply chain and production. A lot of components like "Industrial Internet of Things (IIoT)" systems and physical systems are used for benefitting from such improvements. Physical systems are needed for processing, storage, and collection of data. To make factory efficient and gain the benefits, multidisciplinary techniques are proposed in I4.0 model. Even though some of them have been widely considered, they are still not matured for mass deployment. I4.0 devices can interact with one another automatically to work together and with other remote systems over the web. Figure 3 illustrates the components used in industry 4.0.

Figure 3 – Components for Industry 4.0 for Smart Manufacturing
Source – Achouch et al (2022)

Predictive Maintenance is a recent phenomenon to improve the efficiency and performance of manufacturing processes by improving the equipment lifespan and ensuring sustainable management of operations. When it implies a decline in downtime and a lot of unwanted stops, achieved by reducing repair costs, it provides interventions with prediction of failures. Strategies for smart predictive maintenance are widely used by manufacturers. Predictive maintenance is the recent form which offers highest equipment reliability and longest life, along with most cost-effective and eco-friendly solutions (Figure 4). Proactive maintenance is the approach used to troubleshoot which goes down to the source. This approach is very efficient when it is applied with predictive maintenance.

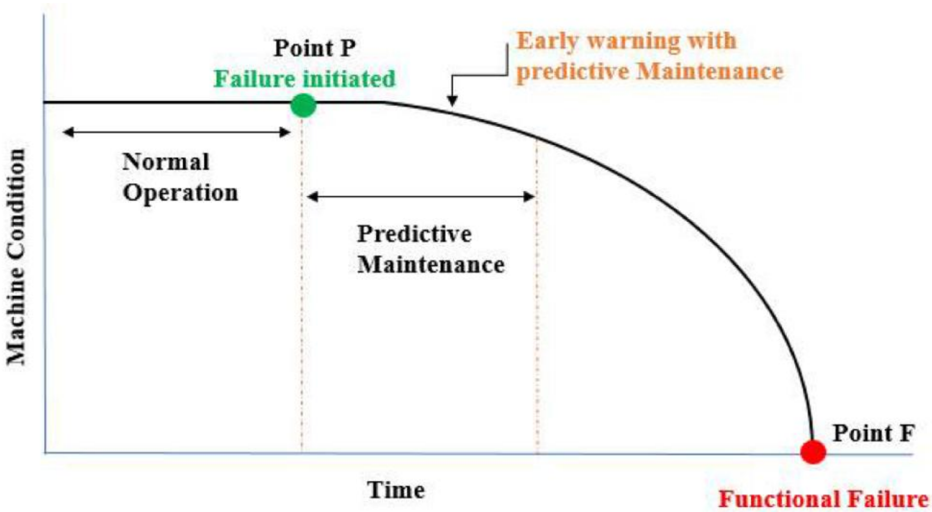

Figure 4 – Diagram of Potential Failure illustrating Predictive Maintenance and Inspection Intervals
Source – Cakir et al (2021)

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Predictive Maintenance Tools and Materials

In the beginning of 21st century, marking the beginning of Industry 4.0, advanced visualization and computational tools have been the important and fundamental components of digital transformation as per latest technologies. Manufacturing companies have been adopted in various industrial applications in maintenance 4.0 or predictive maintenance (Jimenez-Cortadi et al, 2019; Maktoubian et al, 2021). Here are some of the tools used in predictive maintenance -

- **Cyber-Physical Systems** – In smartly connected sensors and production devices, control, diagnostic, and sensing systems, and autonomous monitoring, the most intelligently connected and advanced devices are called as "cyber-physical systems (CPS)" outfitted with different physical and computational tools and models to meet diverse needs of mankind (Okano, 2017). Lee et al (2015) proposed the 5C architecture or 5 stages of CPS architecture" (Figure 5). These steps include simple technique to practice and design cyber-physical systems from the stage of data collection to value generation.

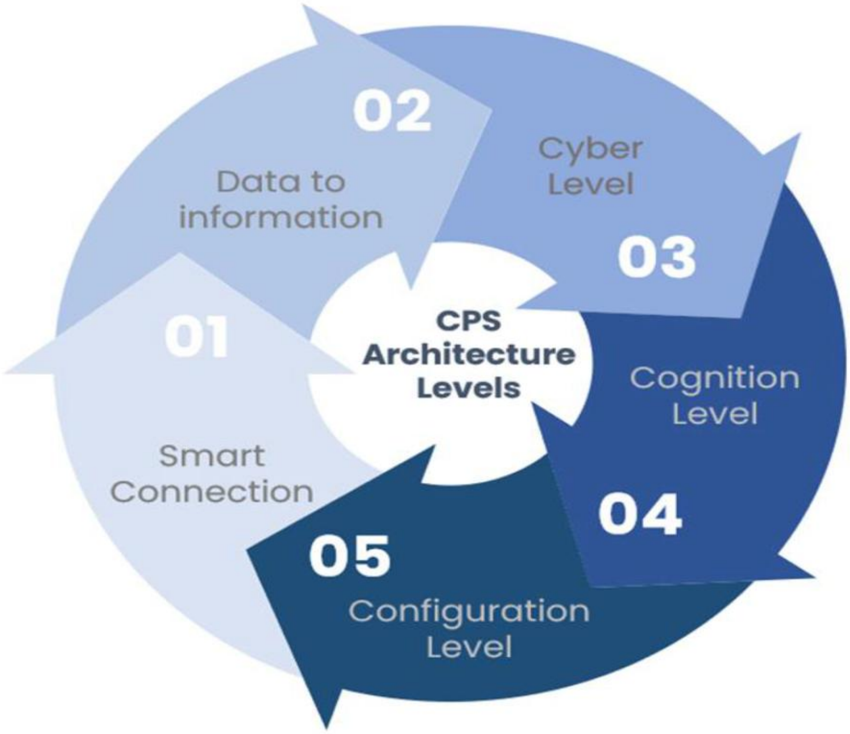

Figure 5 – The 5C Architecture
Source - Lee et al (2015)

- **Industrial IoT** – When it comes to implement IoT applications, the most important step is connecting devices, systems, and machines (Okano, 2017). The concept of IoT offers convenience in industries, also known as "Industrial Internet of Things (IIoT) (Pech et al, 2021) which is the key factor behind Industry 4.0 (Lee et al, 2015). This network offers interaction and interrelation across physical devices and connects CPS systems, enabling retrieval and collection of big data automatically. It results in the notion of big data. IIoT also enables transmission of data over the internet enabling virtualization of resources, cooperation, interconnection, direct access for processing data, machine-to-machine interaction, and intercommunication without human interaction (Lambán et al, 2022).
- **Big Data** – Processing, collecting and analysing big data in real time is a stepping stone for CPS for transforming the maintenance function, especially in terms of failure planning, risk management and prediction (Wang et al, 2022). It can be made possible by optimizing and planning interactions with AI, deep learning, and machine learning or with statistical approaches and models on the basis of data gathered by various sensors (Silvestri et al, 2020). "Volume, Velocity, and Variety" are 3Vs used to characterize big data with other complementary Vs, including Validity/Veracity and Value (Figure 6).

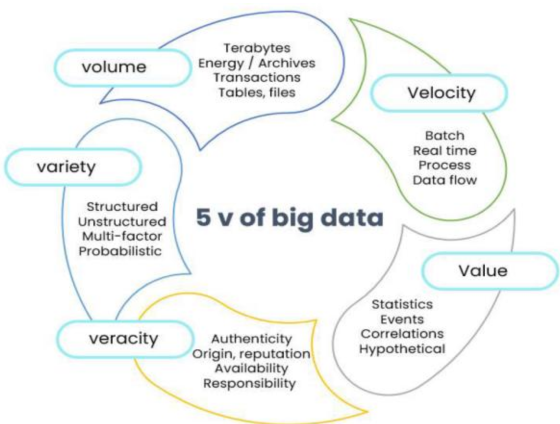

Figure 6 – The 3 Vs of Big Data complemented by Veracity and Velocity
Source –Wang et al (2022)

- **Digital Twin** (**DT**) – It is the virtual or digital copy of products or physical assets. Dr. Michael Grieves was the first to coin the term Digital Twins in 2002 (Kaarlela et al, 2022). This technology was first used by NASA for space exploration (Azeez and Adjekpiyede, 2022). DTs collect real-time information from sensors to connect virtual and real world. Data is either centrally located in a cloud or locally decentralized. Then, data is simulated and evaluated in virtual assets (Hosamo et al, 2022; You et al, 2022). After seeking the information from simulation, parameters are applicable to real assets.
- **Augmented Reality (AR) –** AR is the emerging technology introduced as per VR to generate 3D virtual data with virtual objects or virtual scenes (Wang et al, 2024; Chiang et al, 2022). Then, this information is superimposed into the actual scene to realize the real-world function and improve perception of the user towards real world. AR doesn't need rendering of environment like VR, even though based on VR (Ho et al, 2022; Arena et al, 2022). It has been applied for different processes on maintenance, assembly, etc. As near-zero error rates and high quality are needed in several manufacturing processes to ensure safety and meet user needs, AR can also add immersive interfaces to operators for accuracy, autonomy, and productivity (Liu et al, 2022).
- **Artificial Intelligence (AI) -** To transition to I4.0, Artificial Intelligence (AI) is a robust technology compensating for the ineptitude and lack of traditional approaches and techniques practiced in I4.0 (Daniyan et al, 2020). It is a robust tool to develop smart predictive models in a lot of applications. AI models can manage multivariate and multidimensional data and find hidden data in dynamic and complex environments (Carvalho et al, 2019)". AI is similar to Big Data and is strongly related to it for dealing with weaknesses, answering important questions, and focusing on key issues in processing and analysis.

4.3. Industrial Challenges for Predictive Maintenance

In predictive maintenance, one of the major challenges is developing and designing rooted smart systems to predict and track machine's health. Here are some of the industrial challenges observed in this study –

- Industrialization of the factory has operational and organizational challenges which lead to changes and reforms (Ivanov et al, 2021). Operators should also interact with professionals from different fields. Along with it, organizations should be surrounded with experts or data scientists in the fields for applying solutions.
- It is important to ensure human-to-machine and machine-to-machine interactions in a way that AI doesn't affect functionality of interconnected machines or other equipment in the process of production. Hence, industry must interact with AI systems and other devices. In addition, employees should be adapted or trained to interact with emerging technologies.
- Privacy and cybersecurity are other concerns in industry 4.0. Storage or interconnected technologies are exploited like sensors, IoT, big data, or databases to expose IoT solutions to cyberattacks, usually with malicious software or spamming classification (Tuptuk and Hailes, 2018). In addition, there is no reliable or standard process to secure AI models over attacks.
- Real-time data collection are important elements of predictive maintenance. Data should be secure, massive, accessible, available and qualitative for generalizable predictive maintenance system. Hence, data collection is a significant challenge for organizations as machines or sensors don't generate data on deterioration, conditions, or configurations. A potential solution is labelling all the raw data, event though it needs expert knowledge and can be time-consuming. In addition, operations of labeling consist of a lot of operational and economic cost and risks of errors.
- With multimodal prediction, computer vision, texts, video processing, and sound data in predictive maintenance, data can be gathered from heterogenous systems. Combining all the data is one of the challenges of predictive maintenance for multimodal prediction.
- Another important challenge is adaptability of hybrid and prescriptive modeling in real-time. It is worth developing hybrid and prescriptive models as recommendation system for anomalies, prognosis, and diagnosis of machines. In addition, hybrid models can integrate either both numerical and physical knowledge or limitations of systems with data-based modeling (Wang, 2019). In addition, AI systems can adapt to the entire system while retaining overall performance.
- Explainability XAI – Some of the black box models like RF and CNN are common in predictive maintenance problems. They cannot be intuitive and are not easy to interpret for all stakeholders. This way, explainability is a major factor to accept AI solutions. In addition, new AI trend is based on XAI agnostic approaches designed to understand decision-making making in black-box model and make it easily comprehensible, interpretability, and user-friendly for everyone (Slack et al, 2020). AI systems must support humans in taking over tasks that have low-level thinking.

5. Results

This study is based on in-depth bibliometric analysis which relies on AI approaches for predictive maintenance. Findings of the study provide in-depth analysis to address research questions. The technique of predictive maintenance uses condition monitoring approaches and tools to track the health status and performance of equipment or structure during operations sustainably (Batistakis et al, 2021; Alves et al, 2020; Kirschbaum et al, 2021; Mode et al, 2020). It is worth noting that application of predictive maintenance is based majorly on specific industrial equipment or machine. In predictive maintenance, application of machine learning in I4.0 has showed a lot of potential to improve operational efficiency, optimize asset usage and reduce downtime. There are still several challenges for large-scale adoption which affect large-scale deployment in industries. Though popular in predictive maintenance, adopting deep learning models could be concerning because of their black-box nature. Industries in regulatory environments like healthcare, energy, and aerospace need ML models to offer clear rationales for decision-making, making explainability a major challenge. Another challenge comes from variability in adopting ML across sectors. Choice for specific ML techniques in various areas suggests that solutions for predictive maintenance are usually tailored to meet operational and sector-based needs.
Future studies must cover several important areas in predictive maintenance. They may develop standardized and open datasets to improve accessibility of data, drive innovation, and benchmarking. With lack of labelled data, machine learning approaches must be used to improve model training with a lot of unlabeled data. The key here is to ensure interpretability of models in environments where safety is needed.

6. Conclusion

Predictive maintenance is an exceptional approach in Industry 4.0 to preserve health and operations of industrial plants. Essentially, predictive maintenance relies on its potential to analyze and achieve real-time data to predict when a machine component or equipment will need support or maintenance with ML models. The goal is to improve reliability and service life of machine as much as possible with maintenance activities at the best time for the organization. There are several benefits of Predictive Maintenance. First, it significantly reduces maintenance costs conducted only when it is required. Another benefit is production optimization to predict the fault to organize effective maintenance without stopping production. Additionally, environment and operator safety should be improved to optimize inventory management.
This study analyzes tools and techniques used for predictive maintenance in industry 4.0. By determining a lot of studies published over the past decade, this study identifies some of the emerging approaches in PdM and provides domain-specific knowledge. Predictive maintenance is employed widely in machinery and manufacturing, where it is important to optimize operational efficiency and equipment failures.

References

Rüßmann, M., Lorenz, M., Gerbert, P., Waldner, M., Justus, J., Engel, P., & Harnisch, M. (2015). Industry 4.0: The future of productivity and growth in manufacturing industries. *Boston consulting group*, *9*(1), 54-89.

Jasiulewicz-Kaczmarek, M., & Gola, A. (2019). Maintenance 4.0 technologies for sustainable manufacturing-an overview. *IFAC-PapersOnLine*, *52*(10), 91-96.

Zhu, T., Ran, Y., Zhou, X., & Wen, Y. (2019). A survey of predictive maintenance: Systems, purposes and approaches. *arXiv preprint arXiv:1912.07383*.

Tiddens, W., Braaksma, J., & Tinga, T. (2023). Decision framework for predictive maintenance method selection. *Applied Sciences*, *13*(3), 2021.

Blancke, O. (2020). *Développement d'une approche de pronostic pour les équipements complexes permettant l'application de la maintenance prévisionnelle* (Doctoral dissertation, École de technologie supérieure).

Predictive Maintenance Market Size (2023). Trends Analysis Report By Component, By Services (Monitoring Services, Diagnosis Services), By Participants (Mobile Operators, Devices Vendors), By Region, And Segment Forecasts, 2023–2030. *Grand View Research*.

Zonta, T., Da Costa, C. A., da Rosa Righi, R., de Lima, M. J., Da Trindade, E. S., & Li, G. P. (2020). Predictive maintenance in the Industry 4.0: A systematic literature review. *Computers & industrial engineering*, *150*, 106889.

Zhu, T., Ran, Y., Zhou, X., & Wen, Y. (2019). A survey of predictive maintenance: Systems, purposes and approaches. *arXiv preprint arXiv:1912.07383*.

Wang, J., Zhang, L., Duan, L., & Gao, R. X. (2017). A new paradigm of cloud-based predictive maintenance for intelligent manufacturing. *Journal of Intelligent Manufacturing*, *28*(5), 1125-1137.

Meriem, H., Nora, H., & Samir, O. (2023). Predictive maintenance for smart industrial systems: a roadmap. *Procedia Computer Science*, *220*, 645-650.

Teoh, Y. K., Gill, S. S., & Parlikad, A. K. (2021). IoT and fog-computing-based predictive maintenance model for effective asset management in Industry 4.0 using machine learning. *IEEE Internet of Things Journal*, *10*(3), 2087-2094.

Jakobsson, E., Frisk, E., Krysander, M., & Pettersson, R. (2022, November). A dataset for fault classification in rock drills, a fast oscillating hydraulic system. In *Annual conference of the phm society* (Vol. 14, No. 1).

Tominaga, K., Daimon, Y., Toyama, M., Adachi, K., Tsutsumi, S., Omata, N., & Nagata, T. (2023, September). Dataset generation based on 1D-CAE modeling for fault diagnostics in a spacecraft propulsion system. In *Phm society asia-pacific conference* (Vol. 4, No. 1).

Burkov, A. (2019). *The hundred-page machine learning book* (Vol. 1, p. 32). Quebec City, QC, Canada: Andriy Burkov.

Mitchell, T. M. (1999). Machine learning and data mining. *Communications of the ACM*, *42*(11), 30-36.

Russell, S. and Norvig, P. (2010). *Artificial Intelligence: A Modern Approach*, 3rd ed. Upper Saddle River, NJ, USA: Prentice-Hall.

Berry, M. W., Mohamed, A., & Yap, B. W. (Eds.). (2020). *Supervised and unsupervised learning for data science* (pp. 3-21). Cham, Switzerland: Springer.

Guidotti, D., Masiero, R., Pandolfo, L., & Pulina, L. (2023a). Vector reconstruction error for anomaly detection: preliminary results in the IMOCO4. E project. In *2023 IEEE 28th International Conference on Emerging Technologies and Factory Automation (ETFA)* (pp. 1-4). IEEE.

Ge, Z., Song, Z., Ding, S. X., & Huang, B. (2017). Data mining and analytics in the process industry: The role of machine learning. *Ieee Access*, *5*, 20590-20616.

Guidotti, D., Pandolfo, L., & Pulina, L. (2023b). Detection of component degradation: a study on autoencoder-based approaches. In *2023 IEEE 19th International Conference on e-Science (e-Science)* (pp. 1-2). IEEE.

Nguyen-Da, T., Nguyen-Thanh, P., & Cho, M. Y. (2024). Real-time AIoT anomaly detection for industrial diesel generator based an efficient deep learning CNN-LSTM in industry 4.0. *Internet of Things*, *27*, 101280.

Coutinho, R. W., & Boukerche, A. (2021). Transfer learning for disruptive 5G-enabled industrial internet of things. *IEEE Transactions on Industrial Informatics*, *18*(6), 4000-4007.

Carrera-Rivera, A., Ochoa, W., Larrinaga, F., & Lasa, G. (2022). How-to conduct a systematic literature review: A quick guide for computer science research. *MethodsX*, *9*, 101895.

Kitchenham, B., Pretorius, R., Budgen, D., Brereton, O. P., Turner, M., Niazi, M., & Linkman, S. (2010). Systematic literature reviews in software engineering–a tertiary study. *Information and software technology*, *52*(8), 792-805.

Barja-Martinez, S., Aragüés-Peñalba, M., Munné-Collado, Í., Lloret-Gallego, P., Bullich-Massagué, E., & Villafafila-Robles, R. (2021). Artificial intelligence techniques for enabling Big Data services in distribution networks: A review. *Renewable and Sustainable Energy Reviews*, *150*, 111459.

Nacchia, M., Fruggiero, F., Lambiase, A., & Bruton, K. (2021). A systematic mapping of the advancing use of machine learning techniques for predictive maintenance in the manufacturing sector. *Applied Sciences*, *11*(6), 2546.

Keleko, A. T., Kamsu-Foguem, B., Ngouna, R. H., & Tongne, A. (2022). Artificial intelligence and real-time predictive maintenance in industry 4.0: a bibliometric analysis. *AI and Ethics*, *2*(4), 553-577.

Giannetti, C., & Ransing, R. S. (2016). Risk based uncertainty quantification to improve robustness of manufacturing operations. *Computers & Industrial Engineering*, *101*, 70-80.

Breiman, L. (2001). Random forests. *Machine learning*, *45*(1), 5-32.

Kim, J. S., Kim, J., & Lee, J. Y. (2020). Die-casting defect prediction and diagnosis system using process condition data. *Procedia Manufacturing*, *51*, 359-364.

Ayvaz, S., & Alpay, K. (2021). Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time. *Expert Systems with Applications*, *173*, 114598.

Vapnik, V. (2013). *The nature of statistical learning theory*. Springer science & business media.

Cakir, M., Guvenc, M. A., & Mistikoglu, S. (2021). The experimental application of popular machine learning algorithms on predictive maintenance and the design of IIoT based condition monitoring system. *Computers & Industrial Engineering*, *151*, 106948.

Gryllias, K. C., & Antoniadis, I. A. (2012). A Support Vector Machine approach based on physical model training for rolling element bearing fault detection in industrial environments. *Engineering Applications of Artificial Intelligence*, *25*(2), 326-344.

Salcedo-Sanz, S., Rojo-Álvarez, J. L., Martínez-Ramón, M., & Camps-Valls, G. (2014). Support vector machines in engineering: an overview. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *4*(3), 234-267.

Altman, N. S. (1992). An introduction to kernel and nearest-neighbor nonparametric regression. *The American Statistician*, *46*(3), 175-185.

Jung, M., Niculita, O., & Skaf, Z. (2018). Comparison of different classification algorithms for fault detection and fault isolation in complex systems. *Procedia Manufacturing*, *19*, 111-118.

Achouch, M., Dimitrova, M., Ziane, K., Sattarpanah Karganroudi, S., Dhouib, R., Ibrahim, H., & Adda, M. (2022). On predictive maintenance in industry 4.0: Overview, models, and challenges. *Applied sciences*, *12*(16), 8081.
Jimenez-Cortadi, A., Irigoien, I., Boto, F., Sierra, B., & Rodriguez, G. (2019). Predictive maintenance on the machining process and machine tool. *Applied Sciences*, *10*(1), 224.
Maktoubian, J., Taskhiri, M. S., & Turner, P. (2021). Intelligent predictive maintenance (Ipdm) in forestry: A review of challenges and opportunities. *Forests*, *12*(11), 1495.
Okano, M. T. (2017, September). IOT and industry 4.0: the industrial new revolution. In *International conference on management and information systems* (Vol. 25, p. 26).
Pech, M., Vrchota, J., & Bednář, J. (2021). Predictive maintenance and intelligent sensors in smart factory. *Sensors*, *21*(4), 1470.
Lee, J., Ardakani, H. D., Yang, S., & Bagheri, B. (2015). Industrial big data analytics and cyber-physical systems for future maintenance & service innovation. *Procedia cirp*, *38*, 3-7.
Lambán, M. P., Morella, P., Royo, J., & Sánchez, J. C. (2022). Using industry 4.0 to face the challenges of predictive maintenance: A key performance indicators development in a cyber physical system. *Computers & Industrial Engineering*, *171*, 108400.
Wang, J., Xu, C., Zhang, J., & Zhong, R. (2022). Big data analytics for intelligent manufacturing systems: A review. *Journal of Manufacturing Systems*, *62*, 738-752.
Kaarlela, T., Arnarson, H., Pitkäaho, T., Shu, B., Solvang, B., & Pieskä, S. (2022). Common educational teleoperation platform for robotics utilizing digital twins. *Machines*, *10*(7), 577.
Azeez, N. A., & Adjekpiyede, O. O. (2022). Digital Twin Technology: A Review of Its Applications and Prominent Challenges. *Covenant Journal of Informatics and Communication Technology*.
Hosamo, H. H., Svennevig, P. R., Svidt, K., Han, D., & Nielsen, H. K. (2022). A Digital Twin predictive maintenance framework of air handling units based on automatic fault detection and diagnostics. *Energy and Buildings*, *261*, 111988.
You, Y., Chen, C., Hu, F., Liu, Y., & Ji, Z. (2022). Advances of digital twins for predictive maintenance. *Procedia computer science*, *200*, 1471-1480.
Wang, Y., Yu, T., & Wang, K. (Eds.). (2024). *Advanced Manufacturing and Automation XIII*. Springer.
Chiang, F. K., Shang, X., & Qiao, L. (2022). Augmented reality in vocational training: A systematic review of research and applications. *Computers in Human Behavior*, *129*, 107125.
Ho, P. T., Albajez, J. A., Santolaria, J., & Yagüe-Fabra, J. A. (2022). Study of augmented reality based manufacturing for further integration of quality control 4.0: A systematic literature review. *Applied Sciences*, *12*(4), 1961.
Arena, F., Collotta, M., Pau, G., & Termine, F. (2022). An overview of augmented reality. *Computers*, *11*(2), 28.
Liu, C., Zhu, H., Tang, D., Nie, Q., Zhou, T., Wang, L., & Song, Y. (2022). Probing an intelligent predictive maintenance approach with deep learning and augmented reality for machine tools in IoT-enabled manufacturing. *Robotics and Computer-Integrated Manufacturing*, *77*, 102357.
Daniyan, I., Mpofu, K., Oyesola, M., Ramatsetse, B., & Adeodu, A. (2020). Artificial intelligence for predictive maintenance in the railcar learning factories. *Procedia Manufacturing*, *45*, 13-18.
Carvalho, T. P., Soares, F. A., Vita, R., Francisco, R. D. P., Basto, J. P., & Alcalá, S. G. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering*, *137*, 106024.
Ahmed, U., Ali, F., & Jennions, I. (2021). A review of aircraft auxiliary power unit faults, diagnostics and acoustic measurements. *Progress in Aerospace Sciences*, *124*, 100721.
Shukla, K., Nefti-Meziani, S., & Davis, S. (2022). A heuristic approach on predictive maintenance techniques: Limitations and scope. *Advances in Mechanical Engineering*, *14*(6), 16878132221101009.
Goyal, D., & Pabla, B. S. (2016). The vibration monitoring methods and signal processing techniques for structural health monitoring: a review. *Archives of Computational Methods in Engineering*, *23*(4), 585-594.
Li, Z., Wang, Y., & Wang, K. S. (2017). Intelligent predictive maintenance for fault diagnosis and prognosis in machine centers: Industry 4.0 scenario. *Advances in Manufacturing*, *5*(4), 377-387.
Silvestri, L., Forcina, A., Introna, V., Santolamazza, A., & Cesarotti, V. (2020). Maintenance transformation through Industry 4.0 technologies: A systematic literature review. *Computers in industry*, *123*, 103335.
Ivanov, D., Tang, C. S., Dolgui, A., Battini, D., & Das, A. (2021). Researchers' perspectives on Industry 4.0: multi-disciplinary analysis and opportunities for operations management. *International journal of production research*, *59*(7), 2055-2078.
Tuptuk, N., & Hailes, S. (2018). Security of smart manufacturing systems. *Journal of manufacturing systems*, *47*, 93-106.
Wang, T. (2019, May). Gaining free or low-cost interpretability with interpretable partial substitute. In *International Conference on Machine Learning* (pp. 6505-6514). PMLR.
Slack, D., Hilgard, S., Jia, E., Singh, S., & Lakkaraju, H. (2020, February). Fooling lime and shap: Adversarial attacks on post hoc explanation methods. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society* (pp. 180-186).
Batistakis, D., Xenakis, A., Papastergiou, G., Chatzimisios, P., & Gerogiannis, V. C. (2021, July). An ai-based prediction-as-a-service model for estimating machine bearing health status in industry 4.0 5g applications. In *2021 12th International Conference on Information, Intelligence, Systems & Applications (IISA)* (pp. 1-8). IEEE.
Alves, F., Badikyan, H., Moreira, H. A., Azevedo, J., Moreira, P. M., Romero, L., & Leitão, P. (2020, June). Deployment of a smart and predictive maintenance system in an industrial case study. In *2020 IEEE 29th International Symposium on Industrial Electronics (ISIE)* (pp. 493-498). IEEE.
Kirschbaum, L., Roman, D., Robu, V., & Flynn, D. (2021, June). Deep learning pipeline for state-of-health classification of electromagnetic relays. In *2021 IEEE 30th International Symposium on Industrial Electronics (ISIE)* (pp. 1-7). IEEE.
Mode, G. R., Calyam, P., & Hoque, K. A. (2020, April). Impact of False Data Injection Attacks on Deep Learning Enabled Predictive Analytics. In *NOMS* (Vol. 2020, pp. 1-7).