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# Implementation of predictive maintenance in various Industry: A Review

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**ABSTRACT**

Predictive maintenance has become a crucial approach in the manufacturing industry, offering solutions to minimize downtime, optimize maintenance costs, and enhance operational efficiency. This paper reviews the definition, objectives, benefits, and implementation of predictive maintenance in the manufacturing sector. By leveraging advanced technologies such as the Internet of Things (IoT), machine learning, big data analytics, and cloud computing, predictive maintenance enables real-time monitoring of equipment conditions and failure prediction before they occur. The objectives are to reduce operational costs, increase equipment reliability, and optimize production performance. The benefits include reduced frequency and duration of downtime, lower repair costs, extended equipment lifespan, and improved workplace safety. Case studies discussed show that companies adopting this technology experience increased production efficiency and reduced maintenance costs. The conclusion of this paper suggests that companies invest in technology and infrastructure, develop employee skills, integrate systems, collaborate with technology providers, and conduct continuous monitoring and evaluation. With these steps, companies can more effectively implement predictive maintenance and achieve competitive advantages in an increasingly dynamic market.

**Keywords**: Predictive maintenance; manufacturing industry; Internet of things

## 1. INTRODUCTION

In the era of Industry 4.0, technology plays an increasingly important role in improving efficiency and productivity in the manufacturing sector [1], [2]. One of the emerging technologies is predictive maintenance. Predictive maintenance uses data analysis, sensors, and artificial intelligence algorithms to predict equipment failures before they occur, enabling timely repairs and reducing downtime. This contributes to cost savings and increased operational reliability. Thus, understanding the definition, purpose, benefits, and application of predictive maintenance becomes very crucial in the context of the modern manufacturing industry [3]–[6]. As the complexity of manufacturing equipment increases and the pressure to improve operational efficiency increases, traditional maintenance methods such as preventive maintenance and reactive maintenance are beginning to show their limitations. Preventive maintenance is often carried out based on a predetermined schedule, without considering the actual condition of the equipment. This can result in over-maintenance, which wastes resources, or under-maintenance, which increases the risk of equipment failure. On the other hand, reactive maintenance performed after equipment failure can lead to unexpected downtime and significant loss in production. Therefore, there is an urgent need for a more efficient and proactive approach to maintenance, which can be filled by predictive maintenance [7]–[9].

In the literature, there have been many studies discussing predictive maintenance, but many of them focus on technical aspects, such as algorithm development and sensor technology. Studies that discuss practical implementation and challenges in the field are still relatively few. In addition, there is a gap in the literature regarding the evaluation of the economic and environmental benefits of predictive maintenance, as well as how this technology can be effectively integrated into a broader maintenance strategy.

This article aims to fill this gap by conducting a comprehensive literature review using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method. PRISMA is a structured and transparent method for conducting literature reviews, which allows for the systematic identification, screening, and synthesis of relevant research results. Using the PRISMA method, this article will review various existing studies to understand the definition, objectives, benefits, and application of predictive maintenance in the manufacturing industry, as well as identify future challenges and opportunities. The novelty of this article lies in the systematic and comprehensive approach used to study predictive maintenance, which focuses not only on technical aspects but also on practical implementation aspects and comprehensive benefit evaluation. Thus, this article is expected to provide a significant contribution to improving the understanding and application of predictive maintenance in the manufacturing industry, as well as encouraging further research in this field.

## 2. METHOD

This study used the PRISMA (preferred reporting items for systematic reviews and meta-analyses) method to conduct a systematic literature review on the definition, purpose, benefits, and application of predictive maintenance in the manufacturing industry. PRISMA is a guideline designed to assist researchers in reporting systematic reviews and meta-analyses transparently and completely. This method consists of several main stages, namely identification, screening, eligibility, and inclusion, each of which is designed to ensure that the review process is carried out thoroughly and objectively.

Figure 1 the first stage in the PRISMA method is the identification stage. At this stage, researchers search for and collect relevant literature from various sources, including academic databases such as Scopus, PubMed, IEEE Xplore, and Google Scholar. Keywords used in the search include "predictive maintenance," "industrial maintenance," "machine learning," "sensor technology," and "manufacturing industry." The search was conducted without restrictions on the year of publication to ensure a broad coverage of available research. All studies identified during this search were recorded, including studies published in languages other than English, to ensure comprehensive inclusion.

After the identification stage, a screening stage was conducted to eliminate studies that were not relevant or did not meet the inclusion criteria. At this stage, the title and abstract of each identified study were read and evaluated to determine its relevance to the research topic. Studies that were not directly related to predictive maintenance in the context of the manufacturing industry or that did not provide sufficient empirical data were excluded from the list. In addition, duplicate studies were also removed at this stage. The screening process was conducted by two independent researchers to minimize bias and ensure consistency.

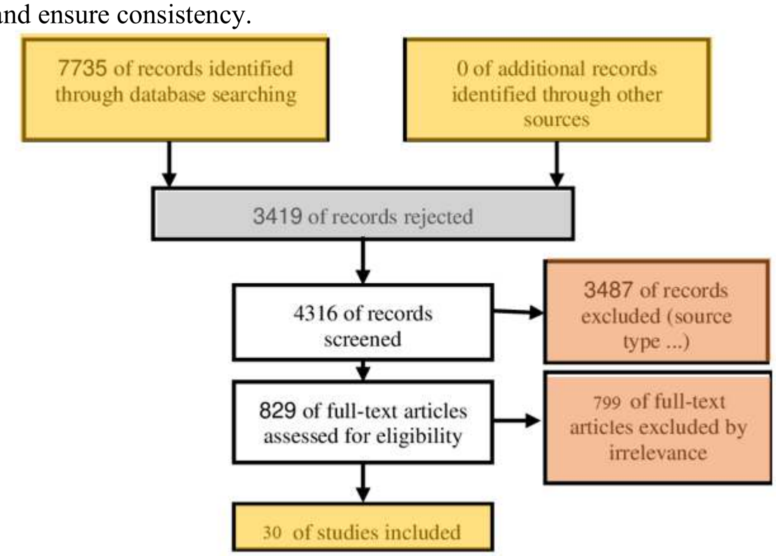


Figure 1. PRISMA flow that has been carried out

The next stage is the eligibility stage, where the full text of the studies that passed the screening was read and further evaluated. Eligibility criteria included clarity of the study methodology, appropriateness to the topic, and the quality and credibility of the data presented. Studies that did not meet these criteria were excluded from further analysis. At this stage, researchers also evaluated the potential risk of bias in the reviewed studies, including publication bias and selection bias. The risk of bias assessment was carried out using validated assessment tools, such as the Cochrane risk of bias assessment tool.

The final stage in the PRISMA method is the inclusion stage, where studies that passed the eligibility stage were included in the final analysis. Data from the selected studies were extracted and qualitatively synthesized to provide a comprehensive picture of predictive maintenance in the manufacturing industry. The extracted data included information on the definition and concept of predictive maintenance, the methods and technologies used, the purpose of the implementation, the benefits obtained, and the challenges and barriers faced. The data extraction process was carried out using a standardized data extraction form to ensure the consistency and accuracy of the data collected.
In the data synthesis stage, researchers organized and categorized the findings from the selected studies based on key themes relevant to the research topic. Qualitative analysis was conducted to identify patterns, trends, and gaps in the existing literature. The researcher also compared findings from different studies to identify consistencies or contradictions in the research results. This was done to provide a deeper understanding of predictive maintenance and to identify areas that require further research.

## 3. RESULT AND DISCUSSION

In the literature review conducted, various studies were found that provide an in-depth understanding of predictive maintenance in the manufacturing industry. The results of this review reveal that predictive maintenance is an approach that can significantly improve operational efficiency and reduce machine downtime. The studies identified cover various aspects of predictive maintenance, from basic definitions and concepts, the technology used, to the benefits and challenges faced in its implementation. Through systematic analysis, these findings not only highlight the great potential of predictive maintenance but also identify research gaps that need to be followed up. In detail, the following are the results of a review of 30 journal articles from 2013 to 2024 that have been selected using the PRISMA method. Table 1 explains the summary of research results related to the application of predictive maintenance. Table 1 analyzes the objectives of each study. The research results are also presented according to the context of the article content. Most of the research results provide positive changes. Details can be seen in Table 1

Table 1**.** Summary of relevant articles

| No. | Identity | Objective | Research result |
|---|---|---|---|
| 1 | Zonta, T., Da Costa, C.A., da Rosa Righi, R., de Lima, M.J., da Trindade, E.S., & Li, G.P. (2020). [10] | This research aims to conduct a systematic literature review regarding predictive maintenance (PdM) initiatives in the context of Industry 4.0. The primary goal is to identify and catalog PdM methods, standards, and applications, as well as discuss current challenges and limitations in PdM. In addition, this study proposes a new taxonomy to classify PdM research areas, taking into account the needs of Industry 4.0. | This research concludes that the ability to predict future asset maintenance needs is one of the main challenges in Industry 4.0. PdM contributes to increased machine downtime, cost control, and production quality. This study also found that a time-based approach is a major challenge in PdM. The proposed new taxonomy helps in classifying research in this area, demonstrating the importance of a multidisciplinary approach that combines computer science and engineering to effectively address the challenges of Industry 4.0. |
| 2 | Carvalho, T.P., Soares, F.A., Vita, R., Francisco, R.D.P., Basto, J.P., & Alcalá, S.G. (2019). [11] | This research aims to present a systematic literature review regarding machine learning (ML) methods applied to predictive maintenance (PdM). The main focus of this research is to demonstrate the ML techniques explored in this field, as well as the performance of current ML techniques in PdM applications. This study also identifies challenges and opportunities in using ML for PdM. | This research finds that ML techniques have become a promising tool in PdM applications to prevent equipment failures in production lines. This study shows that selecting the right ML method is critical for the performance of PdM applications. The results of this review provide a useful foundation on for ML techniques, key results, challenges, and existing opportunities, and support new research in the field of PdM. |
| 3 | Paolanti, M., Romeo, L., Felicetti, A., | This research aims to develop a machine learning (ML) architecture for predictive maintenance, with a special focus on the use of | This research shows that the Random Forest approach has good performance in predicting various machine states with high accuracy. Data is |

| No. | Identity | Objective | Research result |
|---|---|---|---|
| | Mancini, A., Frontoni, E., & Loncarski, J. (2018, July). [12] | the Random Forest method. The system was tested on real industrial examples, involving data collection, data system analysis, application of ML approaches, and comparison with simulation tool analysis. | collected from various sensors, machine PLCs, and communication protocols, which is then analyzed using data analysis tools in the Azure Cloud platform. Preliminary results show that this approach is effective in improving system reliability and reducing economic losses due to unexpected machine failures. |
| 4 | Selcuk, S. (2017) [13] | This research aims to discuss the latest trends and techniques in the field of predictive maintenance, as well as provide suggestions on how to implement a predictive maintenance program in a factory or facility. The primary focus is to improve reliability, safety, availability, efficiency, and quality, as well as protect the environment through a more proactive maintenance approach. | This research finds that predictive maintenance has been adopted by various manufacturing and service industry sectors to increase operational reliability and efficiency. Predictive maintenance techniques that are closely related to sensor technology show increased efficiency, wider application, and more affordable costs. This research also highlights that advances in information, communications, and computing technology, such as the Internet of Things and radio frequency identification, have enabled predictive maintenance applications to become more efficient and common across a variety of industries. |
| 5 | Wang, J., Zhang, L., Duan, L., & Gao, R.X. (2017) [14] | This research aims to investigate a new paradigm of cloud-based predictive maintenance using mobile agents to enable the timely acquisition, sharing, and utilization of information. The main goal is to improve accuracy and reliability in fault diagnosis, remaining service life prediction, and maintenance scheduling. | This research develops a cloud-based sensing and computing node with an embedded Linux operating system, mobile agent middleware, and open-source numerical libraries. The proposed mobile agent approach increases system flexibility and adaptability, reduces raw data transmission, and responds to dynamic changes in operations and tasks instantly. This new paradigm was validated on a motor test system, demonstrating increased accuracy and reliability in cloud-based predictive maintenance. |
| 6 | Lee, J., Ni, J., Singh, J., Jiang, B., Azamfar, M., & Feng, J. (2020). [15] | This research aims to provide a comprehensive overview of the latest efforts and advances in maintenance methods in the manufacturing industry over the past few decades. This research focuses on the importance of intelligent maintenance systems (IMS) which are designed to provide decision support tools to optimize maintenance operations. This research also identifies existing research challenges and directs future research in this area. | This research found that intelligent maintenance systems play an important role in minimizing unplanned downtime, ensuring product quality, reducing customer dissatisfaction, and maintaining a competitive advantage in the market. Intelligent prognostic and health management tools are critical to identifying effective, reliable, and cost-effective maintenance strategies. The results of this review show that despite significant progress, there are still major challenges to be overcome, such as the integration of new technologies and improving prediction accuracy. |
| 7 | Pech, M., Vrchota, J., & Bednář, J. (2021). [16] | This research aims to review the latest literature related to predictive maintenance and smart sensors in smart factories. The main focus of this research is on contemporary trends and future challenges in the application of intelligent sensors for predictive maintenance. This research uses burst analysis, systematic review, keyword co-occurrence analysis, and cluster analysis to provide a comprehensive overview of current trends and classifications in this field. | The research results show an increase in the number of papers related to the main concepts studied, indicating the importance of predictive maintenance continues to grow along with Industry 4.0 technology. This research proposes Smart and Intelligent Predictive Maintenance (SIPM) based on full-text analysis of relevant papers. The main contribution of this research is a summary and overview of current trends in the use of smart sensors for predictive maintenance in smart factories, which provides important guidance for future research in this area. |
| 8 | Ayvaz, S., & Alpay, K. (2021) [17] | This research aims to develop a data-based predictive maintenance system for production lines in the manufacturing sector. This system uses real-time data from IoT sensors to detect potential failures before they occur, by utilizing machine learning methods. | The system successfully identified potential failure indicators and prevented several production outages. Comparative evaluation of machine learning algorithms shows that Random Forest and XGBoost models, which are bagging and boosting methods, provide the best performance in this study. These models have been integrated into the production system at the factory. |
| 9 | Li, Z., Wang, | This research aims to investigate the diagnosis | This system framework consists of five modules: |

| No. | Identity | Objective | Research result |
|---|---|---|---|
| | Y., & Wang, K.S. (2017). [14] | and prognosis of faults in machining centers using a data mining approach in the context of Industry 4.0. This research introduces a system framework based on the Industry 4.0 concept for predictive maintenance in machine centers. | sensor data selection and acquisition, data preprocessing, data mining, decision support, and maintenance implementation. The presented case study shows the application of data mining methods for fault diagnosis and prognosis in an Industry 4.0 scenario. |
| 10 | Dalzochio, J., Kunst, R., Pignaton, E., Binotto, A., Sanyal, S., Favilla, J., & Barbosa, J. (2020) [18] | This research aims to investigate academic advances in failure prediction and predictive maintenance in the context of Industry 4.0. The focus of this research is on the use of machine learning and reasoning, as well as the challenges in implementing them. | This research identifies challenges related to big data such as scalability, latency, and data security. Although predictive maintenance is a rapidly growing topic in Industry 4.0, this research concludes that there are still many challenges that need to be overcome for more effective implementation and use of machine learning and reasoning. |
| 11 | Yu, W., Dillon, T., Mostafa, F., Rahayu, W., & Liu, Y. (2019) [19] | This research aims to introduce a global big data ecosystem for error detection and diagnosis in predictive maintenance using large-scale industrial data collected directly from global manufacturing plants. | This research develops an architecture that addresses various challenges such as big data ingestion, integration, transformation, storage, analysis, and real-time visualization using various technologies such as data lakes, NoSQL databases, Apache Spark, Apache Drill, and Apache Hive. The system was successfully implemented in a real industrial production environment, providing warnings days before an error occurred. |
| 12 | Sezer, E., Romero, D., Guedea, F., Macchi, M., & Emmanouilidis, C. (2018) [20] | This research aims to develop a predictive maintenance architecture based on low-cost principles so that it can be accessed by Small and Medium Enterprises (SMEs). This research focuses on the use of cyber-physical systems (CPS) to monitor temperature and vibration variables in machining processes. | This research produces a cheap and easy-to-develop CPS architecture, which stores data in the cloud and uses Recursive Partitioning and Regression Tree models to predict machine output quality based on temperature and vibration data. Experimental results show promising prediction accuracy in determining the quality of machine output. |
| 13 | Yan, J., Meng, Y., Lu, L., & Li, L. (2017). | This research aims to explore industrial big data processing for predictive maintenance in the context of Industry 4.0. This research proposes a new framework for processing heterogeneous multi-source information. | The proposed framework includes organizing heterogeneous multi-source information, characterization of structured data considering spatiotemporal properties, and modeling of unseen factors. The effectiveness of this scheme is verified through analysis of multisource industrial data for prediction of the remaining life of key components of machine tools, demonstrating improved system reliability. |
| 14 | Sajid, S., Haleem, A., Bahl, S., Javaid, M., Goyal, T., & Mittal, M. (2021) [21] | This research aims to explore the application of data science techniques in predictive maintenance and materials science in the context of Industry 4.0. With the increasing complexity of machines and massive data production, this research focuses on using data science to identify the causes of failures and quality deviations, as well as discovering new elements with desired properties through materials theory and computational skills. | This research identifies five critical processes for data scientists in predictive maintenance through a literature review. Data science uses scientific methods and algorithms to extract knowledge from industrial big data, which can improve the efficiency and reliability of manufacturing systems, as well as predict material quality, reducing costs and production time. |
| 15 | Compare, M., Baraldi, P., & Zio, E. (2019) [22] | This research aims to identify and analyze the main challenges in implementing predictive maintenance (PdM) supported by IoT in the context of Industry 4.0. The focus is on the IoT infrastructure and data management required to support PdM as well as challenges in PHM (prognostics and health management) algorithms. | This research identifies various challenges in the development and implementation of IoT-based PdM, including the integration of IoT technology with data science capabilities to support optimal decision-making. This article presents a comprehensive view of the strengths, limitations, challenges, and opportunities of IoT-based PdM. |
| 16 | Kanawaday, A., & Sane, A. (2017) [23] | This research aims to explore the use of machine learning, specifically the AutoRegressive Integrated Moving Average (ARIMA) model, in predictive maintenance for industrial machines using IoT sensor data. The focus is on applying analytics to machine sensor data to predict | This research shows that the ARIMA model can be used to predict failures and quality defects based on time series data from machine sensors. The application of machine learning in IIoT is proving vital for quality management and quality control, reducing maintenance costs, and improving overall |

| No. | Identity | Objective | Research result |
|---|---|---|---|
| | | quality failures and defects. | manufacturing processes. |
| 17 | Kiangala, K.S., & Wang, Z. (2018) [8] | This research aims to design an experimental method for integrating Industry 4.0 concepts into predictive maintenance for conveyor motors in small bottling plants. The focus is on the early detection of faults or threats to conveyor motors and the creation of predictive maintenance schedules. | This research succeeded in developing a system that monitors motor vibration speed data through vibration sensors, using a Siemens S7-1200 programmable logic controller (PLC). The system generates efficient predictive maintenance plans and enables decentralized monitoring and instant notification via email to maintenance supervisors. |
| 18 | Kamat, P., & Sugandhi, R. (2020) [24] | This research aims to describe the challenges in traditional anomaly detection strategies and proposes a new deep learning technique to predict abnormalities before machine failure in the context of predictive maintenance. | This research highlights the importance of anomaly detection in PdM and how deep learning techniques can improve the early detection of anomalies, enabling manufacturing supervisors to perform timely maintenance activities. The proposed technique successfully identifies anomalies earlier than traditional methods. |
| 19 | Zhang, W., Yang, D., & Wang, H. (2019) [25] | This research aims to present a comprehensive survey of data-driven methods for predictive maintenance (PdM) and their industrial applications, with a focus on machine learning and deep learning algorithms and performance metrics analysis. | This research identifies that most of the data used comes from public datasets and shows a trend of increasing use of deep learning algorithms in PdM research. This research also analyzes the accuracy of various PdM applications, identifies the challenges faced, and guides further developments in data-driven PdM. |
| 20 | Ruiz-Sarmiento, J.R., Monroy, J., Moreno, F.A., Galindo, C., Bonelo, J.M., & Gonzalez-Jimenez, J. (2020) [26] | This research aims to develop a Bayesian Filter-based predictive model to estimate the state of machine degradation in the Hot Rolling process in the stainless-steel industry. This project is part of the innovative SiMoDiM project which focuses on the integration of predictive maintenance systems to improve the maintenance of critical assets in factories. | The proposed predictive model successfully combines expert knowledge with real-time data from the Hot Rolling process, enabling operators to make more informed maintenance decisions. The model has been tested with data from more than 118 thousand processes in real factories, and has proven to be effective in promoting the Industry 4.0 era by improving machine health assessment and predictive maintenance operations. |
| 21 | Susto, G.A., Schirru, A., Pampuri, S., McLoone, S., & Beghi, A. (2014) [27] | This research aims to develop a machine learning-based predictive maintenance methodology that uses a dual classifier approach to minimize downtime and associated costs in maintenance management. The main objective is to generate quantitative health factors and determine their relationship with operational costs and failure risk. | The proposed methodology uses classification modules with varying prediction horizons to provide a performance tradeoff in terms of unexpected disruption frequency and unexploited lifetime. The resulting operational cost-based maintenance decision system succeeded in minimizing expected costs. The effectiveness of this method is demonstrated through simulation examples and maintenance problems in the semiconductor industry. |
| 22 | Schmidt, B., & Wang, L. (2018). [28] | This research aims to improve predictive condition-based maintenance decision making with a cloud-based approach. The primary focus is identifying and tracking condition-related data as well as context data for better utilization of condition monitoring data and machine population-based analysis. | The proposed framework and initial methodology have been tested through case studies aimed at validating its work in the context of real industrial applications. The cloud-based approach enables the collection and analysis of maintenance, production, and plant data from the initial phase through the operations and maintenance phases, increasing the efficiency and precision of maintenance decision-making. |
| 23 | Ran, Y., Zhou, X., Lin, P., Wen, Y., & Deng, R. (2019) [29] | This paper aims to provide a comprehensive review of the latest maintenance techniques, especially Predictive Maintenance (PdM), with emphasis on system architecture, optimization objectives, and optimization methods. This research aims to evaluate existing maintenance techniques and highlight the need for a new maintenance paradigm in the fourth industrial revolution. | This research identifies PdM system architectures, such as PdM 4.0 and Open System Architecture for Condition-Based Monitoring (OSA-CBM), as well as cloud-based approaches. This research also reviews key optimization objectives, such as cost minimization and availability/reliability maximization. Optimization methods including traditional machine learning and deep learning are discussed in detail, indicating future research directions needed to support the application of DL-based PdM techniques. |
| 24 | He, Y., Gu, C., Chen, Z., & | This research aims to develop an integrated predictive maintenance strategy that considers | The proposed integrated PdM strategy combining quality control and mission reliability analysis |

| No. | Identity | Objective | Research result |
|---|---|---|---|
| | Han, X. (2017) [30] | the product quality level and mission reliability state in the intelligent manufacturing philosophy of 'prediction and manufacturing'. The main focus is to integrate key process variables in the evaluation of the equipment degradation state and analyze mission reliability to characterize the production state of the equipment. | successfully minimizes total costs and increases maintenance effectiveness. A case study on a cylinder head manufacturing system shows that this method achieves a cost increase of approximately 26.02% compared to periodic preventive maintenance and 20.54% compared to conventional condition-based maintenance. |
| 25 | Sakib, N., & Wuest, T. (2018)[31] | This research aims to provide an overview of condition-based predictive maintenance solutions aimed at avoiding unexpected and unplanned failures during manufacturing and operational processes. The primary focus is discussing the challenges and opportunities of condition-based predictive maintenance and concluding a summary of future research. | This review identifies challenges in predicting tool damage and degradation, especially in unexpected situations such as shock damage. This research shows that historical data analysis, modeling, simulation, and failure probability play an important role in the development of condition-based predictive maintenance solutions. Challenges faced include data availability, accurate data analysis, and development of more effective prediction methods. |
| 26 | Theissler, A., Pérez-Velázquez, J., Kettelgerdes, M., & Elger, G. (2021) [32] | This research aims to review and categorize research on machine learning-based predictive maintenance in the automotive industry. The main focus is to make the field more accessible to maintenance or machine learning experts, as well as to identify challenges and future research directions. | This research identifies that the availability of public data will increase research activity and that most research relies on supervision methods that require labeled data. Using multiple data sources can improve prediction accuracy. Although deep learning methods will continue to improve, they require efficient and interpretable methods and the availability of large amounts of data. |
| 27 | Ruiz-Sarmiento, J.R., Monroy, J., Moreno, F.A., Galindo, C., Bonelo, J.M., & Gonzalez-Jimenez, J. (2020) [26] | This research aims to develop a Bayesian Filter-based predictive model to predict machine degradation in the stainless-steel industry, especially in the Hot Rolling process. The model is designed to combine expert knowledge and real-time data from the plant to help operators make more informed maintenance decisions. | This predictive model was evaluated using data from more than 118 thousand processes in real factories. The results show that the model is effective in predicting machine degradation, enabling operators to carry out more timely and data-driven maintenance interventions, and encouraging the adoption of the Industry 4.0 paradigm in the manufacturing sector. |
| 28 | Susto, G. A., Schirru, A., Pampuri, S., McLoone, S., & Beghi, A. (2014) [27] | This research aims to develop a machine learning-based predictive methodology using various classification modules for predictive maintenance. The main goal is to adopt dynamic decision rules in maintenance management to minimize operational costs and failure risks. | The methodology is tested using simulated examples and maintenance problems in the semiconductor industry. The results show that this approach can predict maintenance more effectively, reduce the frequency of unexpected breakdowns, and maximize system lifetime by minimizing expected costs. |
| 29 | Schmidt, B., & Wang, L. (2018) [28] | This research aims to improve condition-based maintenance decision-making through a cloud-based approach by utilizing condition monitoring data and contextual data to improve data analysis. | The proposed approach is tested through real industrial case studies. The results show that leveraging cloud-based data and more comprehensive data analysis can improve the reliability of machine condition predictions, as well as provide more accurate and data-based maintenance guidance. |
| 30 | Aivaliotis, P., Georgoulias, K., & Chryssolouris, G. (2019) [33] | This research aims to calculate the remaining service life (RUL) of machine tools using physics-based simulation models and the Digital Twin concept to enable predictive maintenance in manufacturing environments. | The proposed methodology is tested through a case study of RUL prediction of industrial robots. The results show that physics model-based simulations can provide accurate predictions of machine conditions, enabling better monitoring and predictions without using invasive techniques. |

Based on the analysis of the 30 journal articles that have been discussed, we can classify the types of topics into several main categories that cover various important aspects in the development and implementation of predictive and intelligent maintenance systems. The following is a detailed description of the classification of the types of topics along with examples of articles in each category:

A. System architecture and framework:

The discussion of system architecture and frameworks in these articles generally emphasizes the design and the development of systems that support predictive maintenance by utilizing modern technologies such as the Internet of Things (IoT), cloud computing, and advanced data analytics. The main focus of this category is to create a system that can collect, process, and analyze data from machines in real-time to detect and prevent failures before they occur [27], [28], [31], [32].

B. Predictive techniques and algorithms:

Articles in this category focus on the development and testing of various techniques and algorithms for predictive maintenance. These techniques include the use of machine learning, deep learning, time series analysis, and image processing techniques to predict machine failures. The main goal is to improve the accuracy and reliability of failure predictions, thereby reducing downtime and maintenance costs [14],[19] .

C. Applications in specific industries

Many articles discuss the application of predictive maintenance in the context of specific industries. These industries include aviation, manufacturing, automotive, and others. These articles often present case studies or practical implementations to demonstrate the effectiveness of their approach in real-world industrial settings [20].

D. Predictive models and data analysis

This category includes articles that discuss specific predictive models and data analysis techniques used to detect and predict machine failures. Commonly used techniques include regression, artificial neural networks, probabilistic models, and clustering algorithms. These articles aim to develop models that are capable of providing accurate predictions of machine conditions based on historical and real-time data.

E. Challenges and Opportunities in Implementation

Articles in this category discuss the challenges and opportunities associated with implementing predictive and intelligent maintenance in the industry. These challenges include technical issues, data limitations, the need for system integration, and changes in management and organizational culture. These articles also often propose solutions to overcome these challenges and capitalize on the opportunities [10], [13], [14], [16].

Figure 2 classifying these articles into these categories, we can gain a deeper understanding of the various approaches and perspectives taken by researchers in the field of predictive and intelligent maintenance. Each category offers unique insights into how new technologies and methodologies can be applied to improve maintenance efficiency and effectiveness, reduce downtime, and increase machine life. It also helps identify areas that require further research and technological innovation to address existing challenges and capitalize on opportunities available in the development of predictive and intelligent maintenance systems.

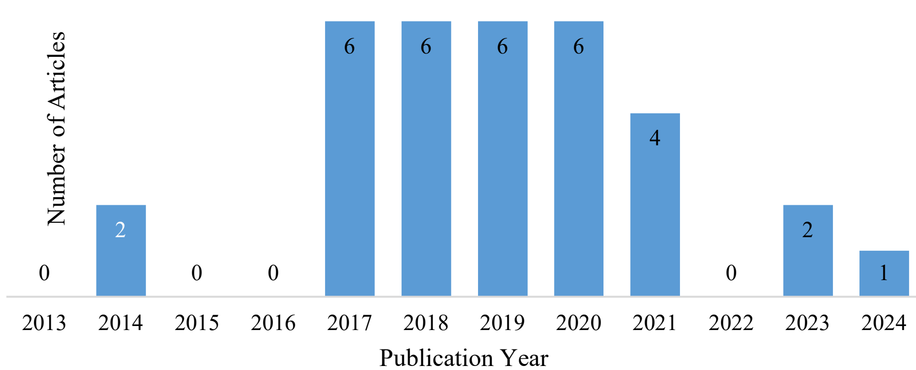


Figure 2. Number of articles by publication year

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The distribution data of selected articles shows an interesting trend related to research in the field of predictive maintenance in the manufacturing industry. It can be seen that there are no selected articles from 2013, 2015, and 2016, which may indicate a lack of relevant publications or an increase in the quality of literature selection in those years. The peak number of articles occurred from 2017 to 2020, with each year having 6 articles. This could reflect an intensive period of research and development in this field, along with the increasing adoption of Industry 4.0 technology and the urgency of predictive maintenance. In 2021, the number of selected articles decreased slightly to 4 articles, 2023 and 2024 respectively as many as 2 and 1 article, this may indicate a shift in research focus or the stabilization of innovation in this area. The years after 2021 show that there are selected articles but the number tends to decrease which may indicate a significant amount of new research in predictive maintenance or that the latest articles have not been published at the time of data collection. Figure 3 This distribution helps identify active periods in predictive maintenance research and can serve as a reference for researchers in evaluating developments and trends in this field.

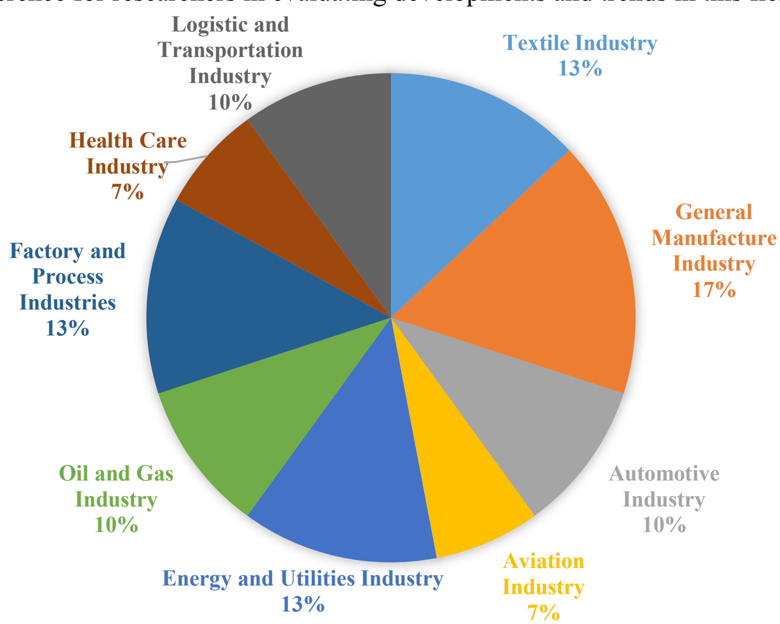


Figure 3. Distribution of industry types discussed in the article

The data presentation above shows that research on predictive maintenance is spread across various industrial sectors, with a fairly even focus. However, there is a higher concentration in the general manufacturing industry, energy and utilities, and the plant and process industry. This indicates that predictive maintenance is a very relevant topic and is widely applied in industries that have high needs for operational efficiency and downtime reduction. Other sectors such as automotive, aviation, and oil and gas also show significant interest, reflecting their specific needs in improving operational reliability and safety through predictive maintenance techniques.

Discussion

In the Industry 4.0 era, predictive maintenance has become one of the key elements that determine operational efficiency and equipment reliability in various industrial sectors. Unlike reactive maintenance which carried out after a failure occurs, or preventive maintenance which based on a fixed schedule, predictive maintenance focuses on real-time data analysis to predict failures before they occur. The use of advanced technologies such as IoT, cloud computing, machine learning, and data analytics allows this approach to provide significant benefits in terms of reducing downtime, and maintenance costs, and increasing machine life.

The implementation of predictive maintenance is not limited to one type of industry. For example, the article "Predictive Maintenance: How Big Data Analysis Can Improve Maintenance" by Jim Daily and Jeff Peterson describes how big data analytics is applied in the aviation industry to improve operational reliability and efficiency. This study emphasizes the importance of integrating cloud-based analytics with industrial machines for more effective data collection and analysis. In the automotive industry, the article "Predictive Maintenance Enabled by Machine Learning: Use Cases and Challenges in the Automotive Industry" identifies the challenges and opportunities associated with the application of machine learning methods for predictive maintenance.

Based on the analysis of the journal articles discussed it can be concluded that predictive maintenance is an important component in improving operational efficiency and equipment reliability in various industrial sectors. Through solid system architecture, the development of effective techniques and algorithms, and successful implementation in various industries, predictive maintenance has been proven to provide significant benefits. However, technical and operational challenges remain, and technological innovation is needed to overcome these challenges and take advantage of the opportunities. Thus, predictive maintenance remains a dynamic and important research area for a more efficient and reliable industrial future.

## 4. CONCLUSION

Predictive maintenance has emerged as a very important approach in the manufacturing industry, providing solutions to minimize downtime, optimize maintenance costs, and improve operational efficiency. In understanding the definition of predictive maintenance, we can conclude that it is an approach that leverages advanced technologies such as the Internet of Things (IoT), machine learning, big data analytics, and cloud computing to monitor equipment conditions in real time. Predictive maintenance focuses on the use of historical data and sensor data to predict equipment failures before they occur, enabling timely maintenance actions and preventing further damage. The application of predictive maintenance in the manufacturing industry has shown significant success in various sectors, ranging from automotive, and aviation, to metal processing. The case studies reviewed show that companies that adopt this technology experience increased production efficiency, reduced maintenance costs, and improved operational safety. For example, the use of machine learning and AI algorithms to monitor machine tool conditions and predict cutting tool wear has resulted in more accurate predictions and more effective maintenance interventions.

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