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RESEARCH & INNOVATION DIVISION
IJIST

Predictive Maintenance in Industrial Internet of Things: Current Status

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Citation | Chaudhary. S, Khan. A. S, Seher. A, Iftikhar. F, Amjad. S, "Predictive Maintenance in Industrial Internet of Things: Current Status", IJIST, Special Issue. 2024 pp 32-44, October 2024
Received | Oct 02, 2024 **Revised |** Oct 07, 2024 **Accepted |** Oct 12, 2024 **Published |** Oct 17, 2024.

Introduction/Importance of Study: Predictive Maintenance (PdM) is a key challenge within the Industrial Internet of Things (IIoT). It aims to enhance system operations by minimizing equipment failures, leading to smoother operations and increased productivity. By anticipating maintenance needs before failures occur, PdM ensures more reliable and efficient industrial processes.

Novelty Statement: This study examines maintenance techniques and datasets that leverage AI and ML for predictive maintenance in the context of industrial IoT. The primary goal is to enhance productivity, identify faults before failures occur, and minimize downtime. By utilizing advanced algorithms, the study aims to improve the efficiency and reliability of industrial systems.

Material and Method: A systematic literature review of state-of-the-art predictive maintenance in the context of industrial IoT, incorporating machine learning (ML) and artificial intelligence (AI) methods, is conducted. This review is based on research articles retrieved from the Dimensions.ai database, covering publications from 2018 to 2024.

Result and Discussion: This comprehensive analysis offers valuable insights for advancing Predictive Maintenance (PdM) strategies in the Industrial Internet of Things (IIoT), ultimately contributing to more efficient manufacturing processes. The study highlights leading publication venues and top keywords in this research area, providing a clear picture of emerging trends. It also explores the prognosis of PdM within the manufacturing industry. Additionally, the review discusses relevant models, methods, input variables, and datasets in the PdM and IIoT domain, with a particular focus on machine learning (ML) and artificial intelligence (AI) techniques. Among the most widely used techniques for PdM in IIoT are deep learning, artificial neural networks, and random forest.

Concluding Remarks: Subsequently, the study highlights various challenges, offering future research directions aimed at refining predictive maintenance techniques.

Keywords: Predictive Maintenance (PdM); Industrial Internet of Things (IIoT); Artificial Intelligence; Machine Learning (ML); Industry 4.0.

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Introduction:

Software maintenance refers to the modification of a software product after its delivery to correct faults, improve performance, or adapt the product to a new environment. In the manufacturing sector, maintenance has long been a major cost driver. In the US, about 33 cents of every dollar spent on maintenance is lost to unnecessary maintenance tasks [1]. With the emergence of Industry 4.0, new approaches have been developed for product maintenance, incorporating components such as wireless and intelligent sensors, big data, and artificial intelligence techniques [2]. Predictive maintenance (PdM) involves anticipating maintenance actions when deterioration or a drop in performance is detected in machine patterns. Recent advancements in AI have been explored in [3], illustrating how AI has facilitated the industrial revolution by automating production processes through big data, cloud computing, cyber-physical systems, and the Internet of Things (IoT). According to [1], manufacturing challenges at Volkswagen led to losses of up to 400 million Euros per week, emphasizing the critical financial impact of maintaining operational production facilities, especially within the data-driven industrial IoT landscape.

In this context, traditional, static maintenance schedules are becoming outdated. The integration of AI and ML models for IIoT maintenance has enabled the adoption of advanced strategies, allowing better assessment of machine conditions before failure occurs. Combining data mining and analytics with ML algorithms allows for effective information extraction, data pattern recognition, and fault prediction [4]. Given the significance of maintenance in the manufacturing industry, this study presents a bibliometric analysis and systematic literature review of state-of-the-art maintenance strategies, with a focus on predictive maintenance.

The paper is structured as follows: first, research objectives are outlined and discussed in the results and discussion section. This is followed by an overview of the background and related work in the domain, along with the research methodology. It covers the evolution of maintenance strategies and previous studies in this area. The subsequent sections present the results and discussion of the bibliometric analysis, followed by a detailed elaboration of the systematic literature review. Finally, the paper concludes with insights into the study's limitations and future research directions.

Objectives:

For an in-depth analysis of predictive maintenance (PdM) in industrial IoT (IIoT), the following objectives are highlighted in this study. These objectives, labeled 1 through 4, guide the research focus, with Objective 1 further divided into four sub-objectives as detailed below:

Analyzing the Trends and Demographics of Studies on Predictive Maintenance in IIoT:

- Investigate the annual number of studies related to PdM in the context of IIoT.
- Examine the types and distribution of publications in this research area.
- Identify the primary venues where PdM research in IIoT is published.
- Analyze trends and clusters of frequently used keywords within the research.

Identifying Key Areas in the IIoT Domain for Applying Predictive Maintenance:

- Highlight the main sectors and industrial applications within IIoT where PdM is being implemented.

Exploring Models Developed for Predictive Maintenance in IIoT:

- Review and evaluate the predictive models proposed and used for PdM in the IIoT landscape.

Assessing Methods, Input Variables, and Datasets in Existing Studies on Predictive Maintenance for IIoT:

- Analyze the methods, types of input variables, and datasets that are commonly utilized in existing studies for PdM in the IIoT domain.

Predictive Maintenance:

According to the Cambridge Dictionary [6], the term "predictive" involves forecasting future events based on existing knowledge, while "maintenance" refers to keeping hardware or software in working condition. Therefore, predictive maintenance (PdM) involves anticipating machine failures before they occur. Authors describe PdM as a system that monitors equipment to detect faults and abnormal behavior, enabling timely repairs [7]. This allows business owners to address repairs or replacements before failures disrupt production [8]. The Smith-Carayon Work System model [9] examines the organizational and human factors in deploying PdM, highlighting key decision-making aspects. The Industrial Internet of Things (IIoT) and PdM have made significant strides in equipment management. Engaging various fields of knowledge to create effective industrial environments, a study [5] utilized deep learning (DL) and the interplanetary file system (IPFS) to develop a reliable, decentralized forecasting framework. Additionally, the advent of Industry 4.0 has transformed maintenance activities by facilitating real-time responses.

Material and Methodology:

The focus of this study is twofold, involving a bibliometric analysis and a systematic literature review of the domain of Predictive Maintenance (PdM) in the Industrial Internet of Things (IIoT). Bibliometric analysis is a quantitative method used to evaluate scientific literature within a specific domain through statistical approaches [10]. This analysis includes citation data, network analysis of authors, institutions, countries, and keyword clusters to identify emerging research trends and potential future directions.

In addition to the bibliometric analysis, a systematic literature review is conducted following the methodology outlined by Kitchenham and Charters [11]. The review also incorporates elements from the PRISMA 2009 Checklist, which details Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [12]. Our primary focus is the IIoT domain, with [13] highlighting the application of PdM across various fields. The review process consists of planning, research, and reporting phases. Specific stages include defining research objectives, establishing inclusion and exclusion criteria, and selecting relevant databases for literature retrieval, as detailed in the following sections. The methodological flow is depicted in Figure 1.

Inclusion and Exclusion Criteria:

The authors evaluated the retrieved literature based on the previously defined inclusion and exclusion criteria. The initial screening comprised 2,539 research articles published between 2018 and 2024. To refine this collection, only journal articles and conference proceedings were retained, resulting in 1,444 articles. The corpus was then filtered based on titles and abstracts. During the title screening, articles that lacked a direct relationship to the terms Predictive Maintenance (PdM) and the Industrial Internet of Things (IIoT) were excluded. Similarly, during the abstract screening, articles that mentioned PdM but did not detail its application within IIoT were removed. Additionally, articles focused on topics unrelated to PdM and IIoT, such as wireless networking, industrial machinery, and sensors, were excluded from full-text screening. This filtration process ultimately reduced the number of articles to 25, which were included for bibliometric analysis. The dataset was exported in CSV and RIS formats for incorporation into the VOSviewer bibliometric software and reference management tools, respectively. After screening, the selected articles were retrieved in full text. The inclusion criteria encompassed journals and proceedings from reputable scientific databases, while the exclusion criteria covered non-English articles and those unrelated to PdM and IIoT, as well as those focusing on wireless networking, industrial machinery, and sensors during the full-text screening.

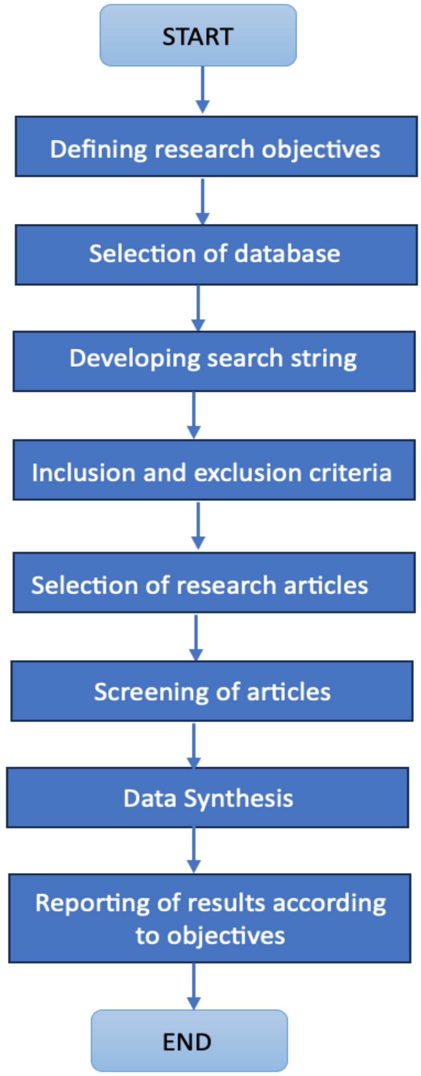

Figure 1. Flow of methodology.

Database and Search Strategy:

This study utilized data from the Dimensions database (https://www.dimensions.ai), provided by Digital Science. This database was selected due to its free access to a comprehensive corpus of data, which can be incorporated into VOSviewer software for bibliometric analysis. Furthermore, research [14] highlights a strong correlation between the citation counts in the Scopus and Dimensions databases, affirming the latter as a viable option for bibliometric analysis. For this analysis, a detailed keyword string was employed, as follows: ((“Predictive Maintenance”) and (Industry 4.0) and (IIoT))

Publication Year: 2018–2024

Publication Type: Articles

We collected the research articles by applying the aforementioned query on March 15, 2024.

Results and Discussion:

Trends and Demographics in Predictive Maintenance:

A research trend of publications from 2018 to 2024 is illustrated in Figure 2, addressing objective 1.1: to investigate the annual number of studies in the domains of PdM and IoT. The data shows an overall increase in published articles from 2018 to 2024, although there is a noticeable decline in publications for the year 2024. This decrease can be attributed to the fact that the query was conducted in June 2024, suggesting that the total number of articles may increase by the end of the year.

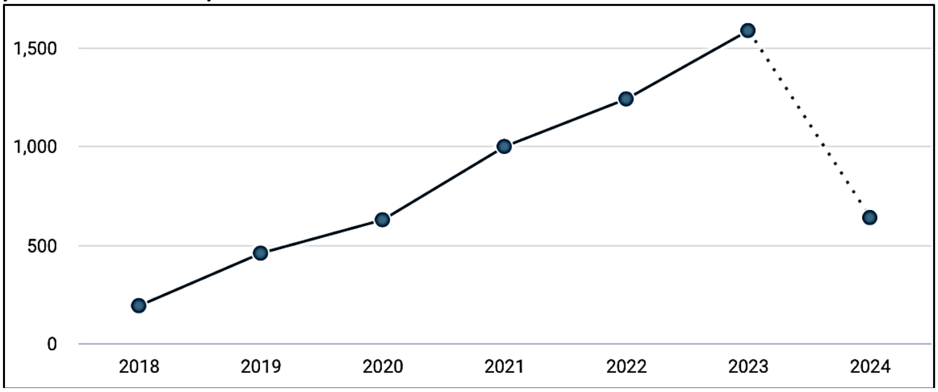

Figure 2. Distribution of publications by year.

Objective 1.2 is addressed in Figure 3, which presents a category-wise analysis of the selected literature. The literature survey comprises data collected from both conference proceedings and journal articles. The analysis reveals that 67% of the corpus is derived from journal articles, while a smaller percentage of 33% originates from conference proceedings."

Bibliometric Analysis:

With the proliferation of scientific databases such as WOS, Scopus, Google Scholar, and Dimensions, bibliometric analysis has emerged as a mature field. Additionally, the tools for conducting bibliometric evaluations have evolved, including Gephi, VOS Viewer, Biblio metrix R, and Bibexcel [15]. This study examines the research area of PdM in IIoT through a comprehensive bibliometric analysis. It employs network analysis to visualize citation patterns, co-authorship occurrences, and keywords related to the field. Furthermore, the study highlights the top journals and conferences for publishing articles, as outlined in objectives 1.3 and 1.4 in the subsequent sections.

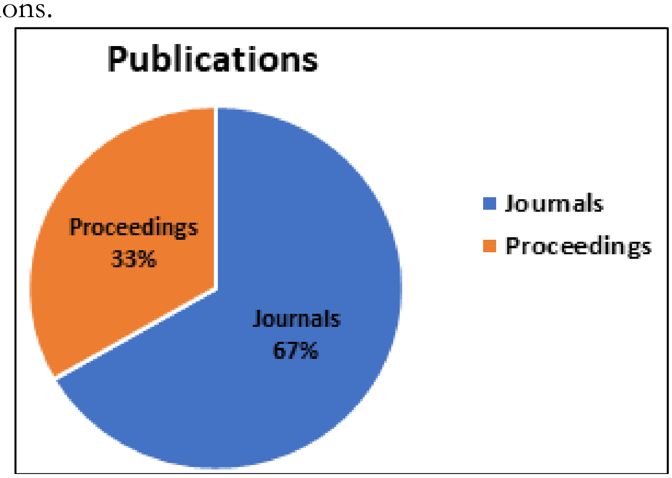

Figure 3. Analysis of corpus according to type of publications.

Objective 1.3 presents the primary venues for publications, with Table 1 listing the top ten venues for articles related to this domain. Notably, the leading journal is *Sensors*, published by MDPI. The initial analysis revealed that these top journals are not exclusively from the highest-tier publications focusing solely on the areas of predictive maintenance (PdM) and the Industrial Internet of Things (IIoT).

Objective 1.4 involves analyzing the trends and clusters of key terms using VOS Viewer, which employs network visualization to illustrate keyword co-occurrence and the relationships between words, as shown in Figure 3. To eliminate data redundancy, duplicate terms were removed during the analysis. The replacement of redundant terms is detailed in Table 2.

Table 1. Top ten venues for publications ordered by citation score.

Name	Publications	Citations
Lecture Notes in Networks and Systems	175	256
Sensors	164	3,665
IEEE Access	149	5,303
arXiv	135	45
Applied Sciences	109	2,407
Lecture Notes in Computer Science	98	331
Lecture Notes in Mechanical Engineering	82	343
IEEE Internet of Things Journal	68	2,609
Sustainability	67	2,007
Procedia Computer Science	66	694

Table 2. Co-occurrence terms filtering.

Label	Replace By
Machine Learning (ML)	Machine Learning
Learning Algorithms	Machine Learning
Internet of Things (IoT)	IoT
Internet of Thing (IoT)	IoT
Industrial Internet of Things (IIoT)	IIoT
Industrial Internet of Things	IIoT

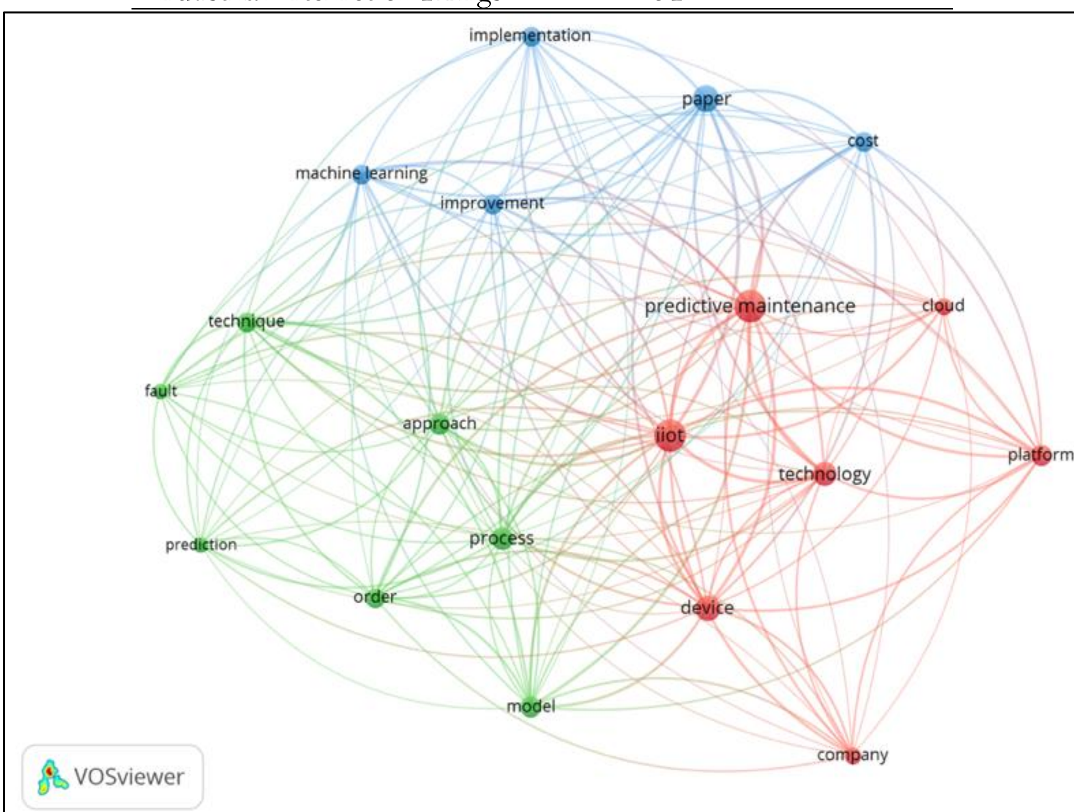

Figure 4. Maps of related concepts generated with terms PdM and IIoT using VOS viewer cluster.

Figure 4 illustrates keyword co-occurrence, with each node representing a concept found in the literature; the size of each node indicates its frequency within the corpus. The most frequently used term is "predictive maintenance," followed by "IIoT." The links between keywords indicate their co-occurrence, with thicker links signifying a higher frequency of simultaneous usage. Highly linked terms include PdM, IIoT, technology devices, and platforms, reflecting the implementation of PdM across various IIoT devices. Different colored nodes represent distinct thematic clusters. Additionally, Figure 3 displays three colors (red, green, and blue) that correspond to three thematic areas explored in this domain, which are further detailed in Table 3.

Each domain comprises underlying research themes. Through bibliometric coupling, we identified three clusters in this area, as illustrated in Table 3. Cluster 1: Maintenance Cluster, which encompasses devices and platforms for implementing PdM in IIoT. Cluster 2: Fault Detection, which relates to terms such as fault detection, predictive maintenance, and associated process activities. Cluster 3: Algorithms, which includes ML algorithms for PdM, along with cost and implementation analyses of these algorithms and their enhancements. These clusters highlight existing terms in the literature and suggest potential future research directions in this field.

Table 3. Cluster of co-occurrences of keywords.

N Cluster	Node
Cluster 1	Cloud, company, device, IIoT, platform, predictive maintenance, technology
Cluster 2	Approach, fault, model, order, prediction, process, technique
Cluster 3	Cost, implementation, improvement, machine learning

Predictive Maintenance in Various Domains of IIoT:

In Objective 2, we discuss key areas of predictive maintenance (PdM) within the context of the Industrial Internet of Things (IIoT). PdM helps reduce costs, improve machine uptime, decrease downtime, mitigate risks, and extend the lifespan of aging assets, making it widely utilized in the manufacturing industry. Its applications span various sectors, including the milling industry [16], fleet systems [17], small and medium enterprises (SMEs) [7], the automobile industry (such as PdM for conveyor belts) [18], car painting processes [19], meat production facilities [20], and wearable technology for monitoring employee activity and equipment performance. Feedback regarding failures is collected and benchmarked, as demonstrated in earlier studies [21]. Predictive maintenance using IIoT and distributed Digital Twins showcases the effectiveness of intelligent sensors in predicting failures early and enhancing business outcomes.

IIoT approaches combined with machine learning optimize maintenance efforts in industrial environments. For instance, [22] developed a system to track equipment movements, perform PdM, and apply various machine learning algorithms while treating each time point as a distinct unit. Utilizing the NASA dataset [22], common models included the Random Forest Regressor, Elastic Net GLM, SVM, and Gradient Boosting Regressor. This system records issues through sensor channels and simulates engine deterioration under various operating conditions.

In Objective 3, we explore the models developed for predictive maintenance in IIoT, focusing on required models and prognosis strategies from previous studies. PdM aims to identify potential problems before they occur, maximizing equipment lifespan and minimizing downtime by analyzing real-time data through techniques such as machine learning, reliability analysis, time series analysis, and failure modes and effects analysis (FMEA) [23]. Key terms include Remaining Useful Life (RUL) and Condition-Based Monitoring (CBM), all part of Prognosis Health Management (PHM) systems [17], which are further elaborated in Table 4.

A case study of an automotive paint shop employs unsupervised learning (PCA, K-Means) and supervised learning (XG Boost, Gradient Boosting Classifier, Bagging Classifier, Grid Search CV, Decision Tree Regressor) for RUL prediction [19]. CBM detects anomalies in sensor data using models such as SVM, LDA, RF, DT, and kNN to signal machinery replacement [27]. PdM implementations also feature Genetic Algorithms for asset management [13], neural networks for assembly line fault detection [18], and various machine learning techniques illustrated in Table 5, including applications for BMW's conveyor belts [25] and humidity level monitoring [20]. Additionally, PdM is enhanced by smart maintenance technologies, incorporating augmented reality (AR) for real-time analytics [28] and an IIoT architecture for CBM [16].

Table 4. Terms for prognosis.

Terms for Prognosis	Articles
Predictive Maintenance (PdM)	[25][26][20][8]
Remaining Useful Life (RUL)	[24][17][19]
Condition Based Maintenance (CBM)	[27][8][28]
Prognosis and Health Management	[24]

Table 5. ML, DL, ANN algorithms.

ML, DL, ANN and Algorithms	Articles
Deep Learning (DL)	[29][26][7]
Random Forest (RF)	[20][27]
Different terminologies related to ANN and ML	[27][17][25][19][30][8][24]

Table 6. Models, methods, variables, and datasets presentation.

Identifier	Description	Case	Dataset	Variables
[27]	Bearing faults detection through predictive maintenance	Electric Motor System	Vibration, temperature, rotational speed, current	Vibration, temperature, rotational speed, current
[8]	Fog computing-based assets identification tracking	Manufacturing Equipment	Recorded date and time, physical assets identification number, error code, electrical voltage, rotational speed, pressure, vibration, components replaced type of equipment, age of the equipment failure	Voltage sensors, pressure sensors, vibrational sensors, rotational sensors
[18]	Anomaly Detection in conveyor car systems	Car Production - Assembly line	Types of sensors, Radio frequency, Range of antenna, Temperature through a sensor, and power of machines	Temperature compliments with sound

[19]	Cloud-based automated paint shop process- car coating process with predictive maintenance	Car Coating Process	Energy consumption, time, color management, fault logs	Energy, colors, time
[20]	Prevent electrical failures due to humidity	Smart Factory (Meat Processing Plant)	Temperature, humidity, particulate matter	Temperature
[24]	Electronic devices for the leading automobile industries. utilization of the hydraulic and pneumatic pressing machine in the manufacturing plant fault detection	Automobile Industry	Machine ID, date, timestamp, target failure rate, actual failure rate, availability system model	Target failure rate by a sensor
[16]	Algorithm for interoperability between different devices for implementing PdM for Cloud-based Systems	Milling Machines	Real-time telemetry data from sensors (time-series), error logs, maintenance history, and machine information preprocessed for the dataset	Rotation, Voltage, Pressure, Vibration
[17]	Cloud-based Fleet Monitoring system RUL determined and visualization on a dashboard	Fleet System	Bearing faults under various operating systems, temperature, speed, and vibration	Temp, load, Rotation Speed, Fault severities
[29]	Fault Detection Predictive maintenance ML solutions	Survey	-	-
[7]	Survey of predictive maintenance in IIoT for SME	IIoT in SME	-	-
[26]	Framework for combining data from different sources of IIoT	Survey	Experts, nodes, sensors	Vibrations, noise
[25]	Implementation of predictive maintenance on encoders	Distributed control system	Speed through sensor	Speed
[28]	Condition-based maintenance complement augmented reality	Electric Monorail System	-	-
[30]	Fault classification, anomaly detection, and live prediction on electric conveyor	Electric Monorail System of BMW group	Normal data and fault data from the test	Fault data through sensors

Objective 4 aims to assess the methods, input variables, and datasets utilized in existing studies on predictive maintenance (PdM) within the IIoT domain. A detailed analysis of the most relevant publications was conducted to address this question, with the findings summarized in Table 6. This table focuses on the descriptions of these significant articles, elaborating on the parameters included in the datasets and the variables collected by the sensors. The analysis indicates that vibration and temperature are the most commonly used inputs from sensors. The study emphasizes that vibrations represent the "language of machines"; if any issues arise in the early stages, vibration patterns can serve as strong indicators of potential future failures [1]. Table 6 highlights opportunities for future research directions, suggesting that additional variables could be integrated into the dataset to enhance the predictive capabilities of PdM methodologies, as outlined in the description column.

Future research could explore the inclusion of various additional input variables from sensors to enhance the efficiency of predictive maintenance (PdM) algorithms. A comprehensive study on sensor technology is essential for effective PdM implementation. Given that PdM is applied across diverse manufacturing domains, each area presents unique characteristics and data set requirements. This aspect warrants detailed investigation through the integration of temperature sensors, vibration sensors, and humidity sensors.

Conclusion:

The primary aim of this study was to analyze predictive maintenance (PdM) within the IIoT domain through systematic literature reviews (SLR) to assess the current status. The paper highlights the existing literature related to PdM, including trends, leading platforms, and key terminologies used in the field. Additionally, it elaborates on the applications of PdM in IIoT, incorporating the necessary machine learning (ML) algorithms. Long sequences can pose challenges for models, as they may struggle to retain information from initial time steps while processing later ones [31]. The research predominantly focuses on techniques such as deep learning (DL), artificial neural networks (ANN), and random forests (RF). The review also details the types of data acquired from sensors, which serve as input datasets, and the specific PdM methods employed, such as Remaining Useful Life (RUL) and Condition-Based Monitoring (CBM).

This study is limited to data collection and analysis from the Dimensions database, which includes a relatively small number of articles directly related to this domain. Furthermore, the analysis was conducted solely using VOS Viewer; a more comprehensive analysis could be performed using Bibliometrix, an R tool designed for extensive science mapping. Additionally, the scope of this study is restricted to English-language articles, and a traditional bibliometric systematic approach was applied. By combining various methods from bibliometric analysis, the results could be enhanced. Future research directions may focus on improving the study by categorizing PdM across different architectures within IIoT.

Acknowledgement: The manuscript has not been published or submitted to any other journals previously.

Authors' Contribution: Each author has made an equal contribution to the study.

Conflict of Interest: There exists no conflict of interest for publishing this manuscript in IJIST.

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