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Comprehensive Analysis of IoT with Artificial Intelligence to Predictive Maintenance Optimization for Indian Shipbuilding

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ABSTRACT- The extensive review of the literature evaluation on predictive maintenance (PdM) in this work focuses on system designs, goals, and methodologies. In the business world, any equipment or system failures or unscheduled downtime would negatively affect or stop an organization's key operations, possibly incurring heavy fines and irreparable reputational damage. Traditional maintenance methods now in use are plagued by a variety of limitations and preconceptions, including expensive preventive maintenance costs, insufficient or incorrect mathematical deterioration procedures, and manual feature extraction. The PdM maintenance framework is suggested as a new method of maintenance framework to prevent any damage only after the analytical analysis shows specific malfunctions or breakdowns, which is in line with the growth of digital building and the advancement of the Internet of Things (IoT), and Artificial Intelligence (AI), and so on. We also present an overview of the three main types of fault diagnosis and prognosis methods used in PdM mechanisms: scientific, conventional Machine Learning (ML), and deep learning (DL). While offering a thorough assessment of DL-dependent techniques, we make a quick overview of the knowledge-based and conventional ML-dependent strategies used in various components or systems. Eventually, significant possibilities for further study are discussed.

Keywords: Indian ship building, Artificial intelligence, Internet of Things, Predictive Maintenance.

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1. INTRODUCTION

A firm's capacity to compete in cheap price, excellent quality, and efficiency is significantly influenced by servicing as a critical business operation with its major effect on expenses and reliability. An organization's main operations would be harmed or interrupted by any unscheduled downtime of industrial equipment, apparatus, or gadgets, possibly incurring heavy fines and irreparable reputational damage. For example, in 2013, Amazon had just 49 mins of the outage, which resulted in $4 million in missed revenue for the company. Following a market survey by the Ponemon Institute, firms lost an average of $138,000 per hr as a result of data centre outages [1] According to some reports, the operation and maintenance (O&M) expenses for wind farms vary from 19% to 28% of the entire income from the power produced, and the maintenance expenses in the oil and gas industry vary from 20% to 65% of the overall price of manufacturing. Consequently, to avoid power failures, obtain greater reliability, and save running expenses, businesses must design an effective maintenance program [2]. (Bevilacqua & Braglia, 2000).

Reactive maintenance (RM), preventive maintenance (PM), and PdM are the three types of maintenance programs that have evolved. Examples of these technologies include the IoT, sensing technology, AI, and so on (See *figure 1*). RM typically produces significant lag and expensive reactive repair expenses because it is only used to return the machinery to its initial working condition after a problem has occurred.

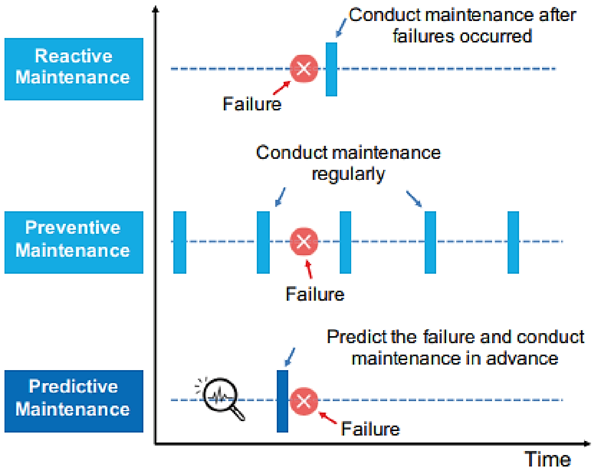

Fig.1: Maintenance plans of RM, PM, and PdM

Although the idea of PdM has been around for a while, it has only gradually seemed to be competent and affordable enough to bring PdM broadly available [3]. Condition monitoring, fault diagnosis and prognosis, and maintenance schedules are frequently included in PdM. The advanced potency of enabling technologies includes the ability to track and anticipate the advancement of faults, recognize, separate, and distinguish precursor and latent faults in equipment and machines, and elements, as well as automate or assist decision-making to create maintenance schedules [4]. Three essential issues should be carefully taken into account from the perspective of PdM:

(1) *PdM frameworks*: With the introduction of Industry 4.0 (I4.0), various approaches, such as enhanced sensing methods, cloud computing, etc., have been used in industrial facilities. PdM structures must: *(a)* be compliant with different manufacturing specifications, *(b)* be simple to incorporate with the developing or forthcoming approaches, and *(c)* achieve the fundamental needs of PdM, such as data gathering, fault diagnosis and prognosis, etc., to develop productive, precise, and ubiquitous maintenance systems by adopting these emerging technologies.

2) *The goals of PdM*: Two common goals for PdM methods are cost and reliability. Insulation is frequently used for these diverse reasons, some of which may contradict. For multi-component processes, for instance, the associated system availability may be weak to be tolerable when the optimum system maintenance expense is reached [5]. Consequently, it is important to thoroughly analyze and establish the PdM goals for a given element or system.

(3) *The methods used to diagnose and forecast faults are as follows*: The currently employed algorithms, including approach-dependent techniques, Artificial Neural Networks (ANN), Support Vector Machines (SVM), Autoencoders, and Convolutional Neural Networks (CNN), among others, differ greatly. PdM problems also vary between distinct industries, factories, and pieces of equipment. The fault diagnosis and prognosis strategies in the framework of PdM should consequently be created and adjusted for certain issues.

1.1 Shipbuilding Industry

Regardless of the worldwide economic and political issues, shipbuilding is one of the earliest, most significant, accessible, and increasingly desirable businesses on the planet [6]. The advantages of the Indian shipbuilding sector include a large coastline, close vicinity to major trade lanes, and low labor costs. On the contrary side, India's shipbuilding capability has fallen behind the nation's economic development, market potential, and human resource capability [7].

Sea transportation is a relevant and sustainable way of transportation that can be combined with other forms to build a cost-effective system. A dependable and active national distribution system that links one location to another, encouraging regional economic development and sustaining an already established economy. The national maritime transportation connection system is designed to integrate cargo and travelers' transportation [8]. Companies that are productive and environmentally friendly can reduce the energy use of their machinery [9]. Industrial cyber-physical systems replace the conventional labor-intensive approach by enabling real-time surveillance, detection, and activation of physical equipment for PdM [10]. The driving drivers in the marine industry are operational effectiveness and ecological responsibility [11]. Lately, it has come to light that the shipbuilding industry is considering using the additive manufacturing (AM) method to manufacture replacement parts on board. Implementation, architecture, and supply-chain structure of AM in the marine industry currently [12].

The maritime sector tries to leverage new technology to get through the current financial crisis and boost its productivity [13]. Furthermore, using these emerging innovations will result in several relationships and perhaps unanticipated effects. Since it is an export-oriented industry that engages highly qualified personnel, mainly depends on cutting-edge technologies, and needs additional capital, international trade in shipbuilding is a main contributor to regional commercial development [14]. Even in the shipbuilding industry, which is notorious for expense permeation and plan procrastination, a much more thorough framework for production supply chains and system implementation requirements that involve providers at the minimal stages can serve to stimulate expenditure in good standards. This study explores prescriptive and strategic objectives for intended and practical aspirations in the marine shipbuilding sector from the standpoint of sustainability improvement [15].

Marine PdM parts can need to be replaced while they are still in use during their scheduled or regular service intervals, which would be expensive. Utilizing sensor or ML techniques in the IIoT framework, it is the potential to optimize the maintenance of maritime mechanical systems. AI-based PdM uses a variety of data sources to determine which components ought to be upgraded before they fail, including manufacturing methods, environmental data, and data from integrated IoT sensors in equipment.

The shipbuilding sector needs physical labor for Industrial Internet of Things-based PdT-as-a-Service (IIoT-PdMaaS). Most goods are transported by sea and water transport worldwide, and this fact has long been acknowledged by all. Ship maintenance is extremely important to maintain ships' conditions at a reliable operating level. The plan for ship maintenance is shown in *fig.2*.

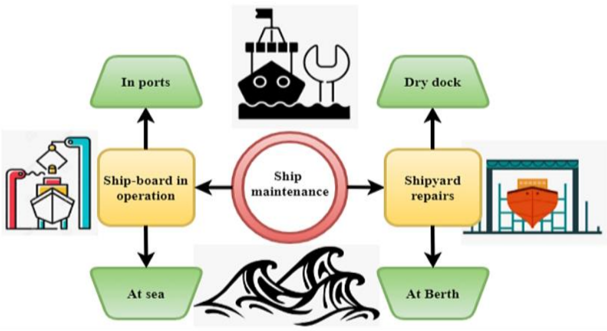

Fig. 2: Maintenance strategy for ships

1.2 Research Objective

The main objective of this studies is listed below:

(a) This paper's major aim is to conduct a comprehensive literary evaluation aimed at addressing the subsequent study question:
(b) What benefits and opportunities do AI technologies bring to IIoT applications in Industry 4.0, particularly for PdM?
(c) Rather than focusing on the results that the researchers provided, a preference was placed on evaluating the state-of-the-art techniques, together with their attributes and techniques.

2. LITERATURE REVIEW

As part of the industry 4.0 revolution, recently founded additive AM technologies may be useful for producing labor-intensive and complex items. The shipbuilding industry might make intricate double-curved components with greater design flexibility and at a cheaper cost by utilizing Wire Arc Additive Manufacturing (WAAM) [12]. The research looked at existing and future WAAM uses in the shipbuilding sector and talked about how the technology might be used given some current and possible limitations like resource accessibility and property standards, design complexity, and organizational procedure. The rapid surge of the shipbuilding industry is an effort to increase future prosperity. As the shipbuilding industry grows and demands improved quality of the product, standard costing as a means of cost information would be put to the test. By employing operations to determine expenditures, the Activity-Based Costing (ABC) System produces overhead expenses that are more pertinent and organized [16].

Design errors could result in major cost overruns in the shipbuilding sector. It's easier to guarantee speedy delivery and higher efficiency, when possible, and design problems are anticipated. Additionally, the rule aggregation procedure that enables the aggregation of discriminatory classification rules was not sufficiently considered by conventional associative classification approaches (ACA) [17]. In addition to finding specific rules that effectively aggregate pertinent authorities and use less fuel, the number of similar attributes was also considered to improve predictive accuracy. It cost money and took months to construct a new ship. Consequently, selecting a shipyard involves knowledge of the industry on the part of the shipowners [18].

The purpose of this research was to distinguish between qualified and unqualified shielded metal arc welders (SMAW) in the shipbuilding sector. To reduce examination expenses while guaranteeing weldment grade and requiring minimal preventative maintenance, an economical tool that could rapidly evaluate a welder's level of ability was needed [19]. Without PdM, smart manufacturing in the industrial sector and components with dehumidifying pumps used for anticipations of boats in shipyards would not be conceivable. In shipyards with smart manufacturing in I4.0, ML technologies have become a practical tool for PdM and dewatering equipment. The scholars examine the literature on ML techniques like SVM for PdM in I4.0 and categorize the research relying on the ML algorithms, machinery, and equipment used in data collection and organization [20].

The article is applied research of the conventional shipbuilding sector, its providers, and consumers in Indonesia, and it offers suggestions for enhancing the efficiency of the supply chain [21]. The conventional shipbuilding industry, the providers, and the specific provider ratings make up the three aspects of this research. To enhance the efficiency of other industries, management lessons can be learned by looking at supply networks for the shipbuilding industry. The IIoT-PdMaaS strategy has been proposed to outperform the current approaches. Enhancing organizational procedures, resource management, fuel efficiency, delay times, and PdM in shipbuilding has been advised by the IIoT-PdMaaS strategy.

3. METHODOLOGY

To acquire consistency and high-quality outcomes, we built this study on the notions of literature review.
The primary scientific issues that this analysis will focus on are:

- make a taxonomic suggestion for preventive maintenance;
- compile the key ideas concerning the subject;
- list the primary surveillance and prediction models used in the sector;
- pinpoint the company's primary problems and upcoming problems.

3.1 Research Questions

We formulate the major question (MQ) and sub-questions (SQ) in *table 1* based on the highlighted scientific contributions and difficulties.
To report on how PdM is being applied in the industry, we create MQs. The SQs work together to describe the review's contributions to science. The primary methods for sharing research on the PdM and industry are listed in the SQ1 question. The techniques and concepts utilized are identified and related in SQ2. The SQ3 analyses the most frequent terms to standardize and give a taxonomy suggestion. The SQ5 inquiry mentions the difficulties and potential future directions after SQ4 examines the applications.

Table 1: Research questions

Identifier	Problems
MQ	What concepts, techniques, or monitoring-related framework is currently being used in the market?
SQ1	What are the primary channels for getting PdM-aligned research out there in the business world?
SQ2	Which prediction methods are most frequently used in the sector?
SQ3	Is it feasible to develop a classification utilizing the phrases discovered for surveillance or predictive applications?
SQ4	How do the survey results for concepts, approaches, or design look?
SQ5	What issues and unanswered questions have been noted?

3.2 Search Strategy

The datasets and strings were defined in the following phase. Since Google Scholar provides a complimentary search of the publication's title and contents, we picked it as our opening dataset. Our goal is to produce a larger number of results, even though some of the publications' returns are not centered on PM. It would be an opportunity to assess the string's efficiency and spot any possible PdM-related categorizing challenges. Due to the difficulties and perspectives, this investigation line will face shortly, we have narrowed our lookup to PdM deployed to Industry. The string considers various characteristics that have been identified, like the premise that PdM approach data is dominated by electrical and mechanical parameters. Our study's string of conclusions is shown in *table 2*.

Table 2: Quality evaluation standards

Section	Depiction
Criteria 1	Search with a 12-year filter from 2008 to 2020.
Criteria 2	Eliminate all books, scientific documents, theses, and dissertations.
Criteria 3	Delete any articles that are fewer than four pages long or not in English.
Criteria 4	Eliminate any articles with titles, abstracts, or keywords that do not contain the keywords industry, intelligent factory, smart and smart manufacturing, or IoT.
Criteria 5	Eliminate any articles that don't discuss surveillance or forecasting as a paradigm, technique, or design for industry, smart factories, or IoT.

3.3 Article Selection

The string shown in *fig.3* was performed at Google Scholar on September 13, 2020, with a filter that took ten years, from 2008 to 2020, outlawing copyrights and quotations. The papers were then transferred to Mendeley software. The goal of our assessment was to increase the number of outcomes that were sent to the database while also assessing the string's context and the MQ and SQ inquiries.

"MONITOR" or "PREDICT"

"ARTIFICIAL INTELLIGENCE" or "AI"

"INTERNET OF THINGS" or "IoT"

"MODEL" or "METHOD" or "ARCHITECTURE"

Fig. 3: Search string

We changed the string to reflect the basis of publishers after the cataloging was done in Google Scholar. We continued the methodology in that sequence, removing identical publications as we go.

The selected style must be highlighted. As a team of investigators cataloged the literature, the first choice was made by identical dissemination of the papers and regular meetings to explain the findings. After analyzing roughly 100 articles, we found that some searches had delivered material that did not meet criteria 5. (See *Table 3*)

After the initial selection, 120 papers were chosen using a methodology that considered abstract analysis, keyword research, section content analysis, and conclusion verification. The important requirement used in these was the 5, and we verified whether the paper helped with the application of the PdM while considering time-based monitoring rather than just an alert.

We searched for articles with relevant content to include in the remainder of this discussion as well as other research surveys, evaluations, mapping, and particles that emphasized business concerns and trends connected to PdM as our final application of the criteria.

Table 3 lists the articles that were chosen along with the categories of publications, publishers, conferences, or journals that were included in our corpus.

Table 3: Selected articles sorted by year

Article	Publisher	Year
[22]	IEEE	2017
[23]	ASME	2017b
[24]	ASME	2017c
[25]	ASME	2017a
[26]	Elsevier	2017d
[27]	Elsevier	2017
[28]	IEEE	2017
[29]	Elsevier	2017
[30]	Elsevier	2017
[31]	IEEE	2018
[32]	IEEE	2018
[33]	Springer	2018
[34]	IEEE	2018
[35]	Elsevier	2018
[36]	IEEE	2018
[37]	Elsevier	2018
[38]	IEEE	2018
[39]	ACM	2018
[40]	Springer	2018
[41]	Springer	2018
[42]	Elsevier	2018
[43]	IEEE	2018
[44]	Elsevier	2018
[45]	IEEE	2018
[46]	Elsevier	2018
[47]	IEEE	2018
[48]	Atlantis-Press	2018
[49]	IEEE	2018
[50]	Springer	2018
[51]	IEEE	2018
[52]	Taylor & Francis	2018
[53]	IEEE	2019
[54]	Springer	2019
[55]	Elsevier	2019
[56]	IEEE	2020
[57]	Elsevier	2020
[58]	Elsevier	2021
[59]	Springer	2021
[60]	IEEE	2022
[61]	IEEE	2022
[62]	IEEE	2022
[63]	Elsevier	2023
[64]	IEEE	2023

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4. RESULTS AND DISCUSSIONS

To reply to the MQ, we give the findings and analyses in this section based on the previously discussed questions.

SQ1 —What are the primary channels used in the industry to spread PdM-aligned studies?
We analyze the following to respond to this query:
1. Table 3, which includes a list of each study's conferences and journals;
2. Fig. 3, demonstrates the distribution of the article by publisher.

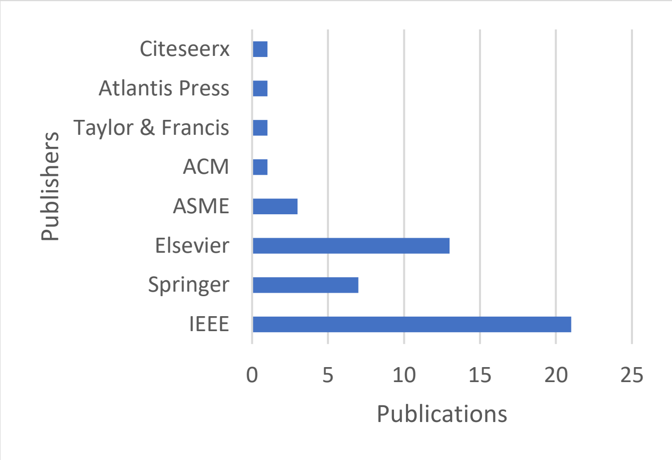

Fig. 4: Distribution of publications by Publisher and Type.

With the help of bar graph in *fig. 5*, we can identify IEEE and Elsevier with the greatest quantity of articles. The distribution of publications analyzed using published methods confirms the finding that PdM applications exhibit an interdisciplinary quality involving numerous fields of study.

The annual rise of articles is depicted in *fig. 4* with a focus on the year 2020. The development of IoT and AI for PdM in the industry is a contributing element, which we emphasize.

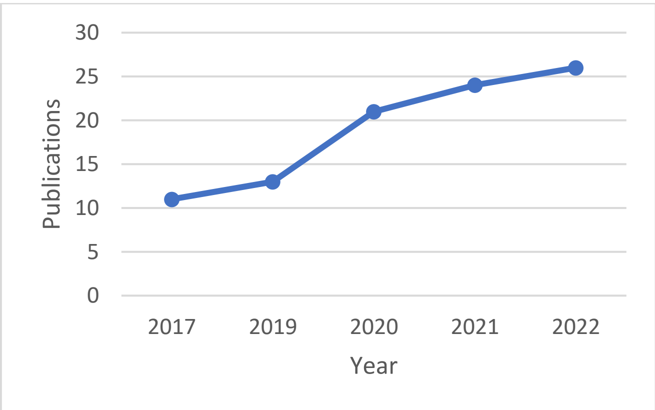

Fig. 5: Distribution and tendency of articles by year

IEEE and Elsevier are the primary channels for propagating PdM in the enterprise, as can be seen in the figures. The line separating conferences and journals is razor thin. The articles indicate a sharp increase in 2020, which suggests a pattern for the years after. Another thing we can bring out is that a lot of PdM approaches come from journals that have an overall score for engineering, but not computing.

SQ2 — Which prediction methods are most frequently used in the sector?
We presented the subsequent responses in several situations when the articles were assessed: We start by going into detail about the three prediction categorization techniques: data-driven, knowledge-based, and physical model-based.

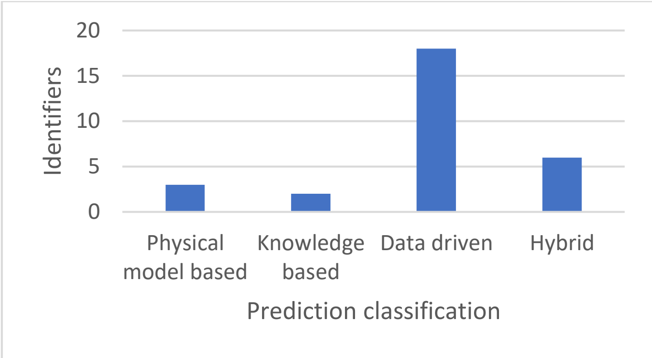

Fig. 6: Classification of the prediction

The second setting in which to answer SQ2 concerns ANN, ML, and algorithm-based solutions. For this purpose, we separate the papers into three major blocks: Deep Learning (DL), Random Forest (RF), and additional ANN and ML-based approaches.

Table 4: List of the chosen articles

Algorithms	Identifiers
RF	[23] [24] [25] [26] [37] [49]
DL	[28] [32] [42] [45] [48] [49]
ANNs and ML	[26] [28] [31] [34] [35] [43] [46] [51]

SQ3 — Is it feasible to build a classification utilizing the phrases discovered for surveillance or predictive applications?
By resolving one of the scientific difficulties of this study, we responded to this query. With the completion of the investigation and the description of the publications, we began the identification, separation, and analysis of the findings, demonstrating the methodology's sequential application. To do this, we use the VOS viewer tool to add to the visualization of the key terms discovered and produce a taxonomy that is more thorough than we had originally intended.

As per *table 5*, we have implemented filtering for comparable phrases to prevent duplication. This method avoids plotting the interpretation of identical words written differently or even writing, individually, on the map.

Table 5: Configuration file for discriminant terms

Initialing	Changed by
Learning algorithms	ML
Internet of Things	IoT
Predictive maintenance	Maintenance
Artificial intelligence	AI
Deep learning	DL

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SQ4 — How do the survey responses for designs, approaches, or structures look?

The topics about applications provide an overview of the key data regarding the models, approaches, structures, and designs. We emphasize the article's headline or executive summary, the implementation scenario, and the data used to create the projection. Each publication has an eccentric characteristic, like the use of sensors, acquisition, connectivity, or return form, but most applications have an issue with the existing plants, which is one of the largest obstacles for those looking to enter a sector with limited resources.

SQ5 — What issues and unanswered queries have been noted? Implementation of time-based PdM is the study's main obstacle and emphasis. Even the chosen publications, which paid attention to these criteria, do not explicitly state that they will make the forecast. RF was used in one example to anticipate a failure window of seven days [49]. Other conditions include reactive mode, planned maintenance, planned preventive actions, and planned condition monitoring, among other time-related designations.

6. CONCLUSIONS

To acquire the requirements of excellence, safety, and efficiency, the maintenance action involves planning and strategy. We are aware that one of them predictive maintenance will be the aim of our research, in which we hope to better understand the methodology used and the programs now in use. A summary of PdM from the perspective of Industry is thus intended by the existing literature offered in this paper. 47 articles on technologies, frameworks, and techniques associated with the use of PdM were found to be the significance of our extensive bibliographical survey approach. We drew attention to the multidisciplinary nature of the industry's new issues and the need for integration. The area of investigation that can be expanded along with the concepts introduced by the FIS principle, and that implementation will significantly alter and enhance the industrial environment.

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