A Review on Equipment Health Monitoring Using Machine Learning Techniques

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Abstract. Numerous scientific domains have been impacted by current developments in ML, AI and the industrial IOT. It has generated a sea of opportunities for embedding sensors that can be tracked and utilized to gather data practically anywhere. Every area of business, particularly smart manufacturing technology since it began to embrace the Internet of Things, has been highlighted by machine learning models. Instead of adhering to a regular timetable, predictive and preventive procedures are being used to better care for the machine. Within the parameters of this study, we may concentrate on the critical procedures of machine or component failure prediction in the smart industry. The most recent advancement in solutions built on machine learning is also pre sented. This can be accomplished by monitoring the machine on the assembly line and installing various sensors so that data can be obtained from those sensors and properly formatted before being utilized to train the machine using supervised machine learning model. Additionally, the historical data on machine failure can be utilized to forewarn about impending machine failure or breakdown in order to stop the entire production or assembly line from shutting down. Additionally, the obtained data can be used with the ML outlier identification technique.

Keywords: Failure prediction · machine learning · production · Industry 4.0 · and unexpected downtime

1 Introduction

1.1 Research Background

A current issue called "Industry 4.0" has an impact on all of today's factory output. Industry 4.0 is all about connectivity, not the mass production model that dominated the second industrial revolution, the steam engine and machinery that powered our factories during the first, or even the rise of new of computer-driven systems during the machine age, which is the one we are currently living via. It's an opportunity to dramatically change how business reacts to social demands. A linked, futuristic environment will be the driving force behind Industry 4.0's development. Prospects for significant upheaval exist, and individuals who are left behind will feel it strongly. With the use of sensors, networking, artificial intelligence methods, machine learning, CPS, and other technologies,

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industry 4.0 refers to the creation of autonomous robots, smart inventory management systems, and smart supply chain management. The use of internet technology and i4.0 techniques is expected to have a substantial positive impact on small and medium-sized firms' growth and prosperity.

1.2 Industry 4.0

I4.0 is currently a very hot issue in both academia and industry. Three German engineers and the German government supported the first promotion of this word. It promises to close the industrial divide between the physical and digital worlds. Industry 4.0 aims to connect the entire globe digitally and bring digital power into the industrial sector. A full-fledged Industrial Revolution, which has the potential to greatly enhance lives and create new possibilities for many people across numerous industries, can also be understood as the concept of Factory 4.0.

The Ir 4.0 idea and the Smart Factory paradigm are closely related since intelligent communication between various industrial units is one of their main points of interest. IoT is a concept that evolved from the more well-known Internet of Things concept, and there are a growing number of uses for it. Iot aims to connect computers, controllers, actuators, and sensors to the Internet in order to facilitate information sharing among all involved parts. This information interchange can serve as the foundation for creating intelligent services in the future that have a strong chance of improving the existing levels of productivity and adaptability found in industry.

Due to the lack of sustainability within the sector, several innovations are focused on the aforementioned fields, and research is constantly spreading out and expanding with new ideas, sometimes without any real hope of seeing the studies come to fruition. Losing the actual link to the current IoT/Industry4.0 concepts, as well as the development directions established by the majority of the most important successful research movements and industrial representatives in the sector, is the root cause of this problem. A systematic and well-structured viewpoint over the state-of-the-art is required to resolve these problems.

Since the first announcement of Ir 4.0 by the German government at the Hannover Fair in November 2011, it has grown significantly in popularity and significance. Each industrial revolution has as its primary objective increased productivity. As demonstrated in Fig. 1, the invention of steam power, which helped to boost production, sparked the first industrial revolution. The second industrial revolution occurred when energy was used to boost efficiency. The third technological revolution began as a result of the use of electronics and information technology to boost productivity and efficiency.

A new industrial sector being created by Ir 4.0 will rely on data interchange and data collecting along the whole supply chain. Industry 4.0 is a new method for combining the physical and digital worlds simultaneously. Oesterreich et al. further define Industry 4.0 as "the production environment's expanding digitalization and automation as well as an extended communication made possible by the development of a digital value chain" Pereira and Romero [2] define Ir 4.0 as a "umbrella term for a new industrial paradigm" that encompasses Cyber-Physical System (CPS), Internet of Things (IoT), Internet of Services (IoS), Robotics, Big Data, Cloud Manufacturing, and Augmented Reality. The

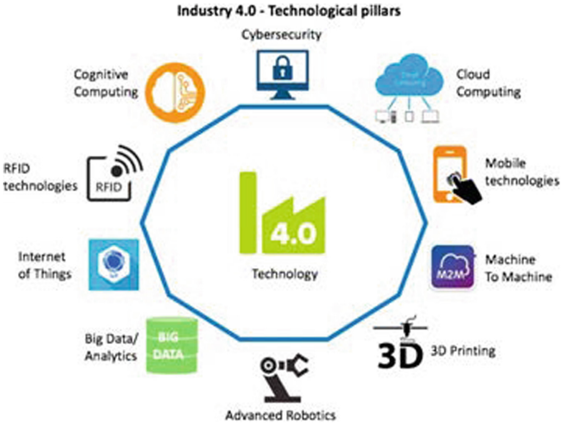

Fig. 1. Concepts of Industry 4.0

two segments that follow will introduce the foundational technologies of Ir 4.0 as well as the challenges that come with implementing it [1].

1.3 Issues Facing the Industry 4.0

- Training
- Work Organization and Process Type
- Supplier of mechatronic systems and equipment lacking in research and expertise
- High-quality network infrastructure and cyber security
- Optimal plant layout

1.4 Machine Learning for Predictive Upkeep

An organized procedure with discrete steps happens once ML is put to PdM. Creating models that accurately predict maintenance results while utilizing more efficient data collection and usage methods is the aim. The process of collecting data consists of choosing and which was before past data. Historical data refers to information from previous working cycles.

The success of ML models in PdM applications depends on the IoT network. Data from the sensors is provided through this network, analyzed, and dispersed throughout the database so that the model may utilize it to estimate maintenance needs. In order to facilitate data transmission inside the network and to enable communication between the various sensors and devices, protocols are used. Without IoT, it would be impossible to gather and store a variety of sensor data points, which is necessary for the successful implementation of ML in PdM. The selection of the historical data phase and model maintenance are two more essential aspects that distinguish traditional ML models from models created for PdM. The relevant phases of conventional machine learning models take the form of preprocessing the data, selecting a model, training it, and validating it.

The current study outlined the major characteristics and ideas of Ir 4.0 and the Industrial Internet while emphasizing the similarities between them.

Both paradigms are currently generating a lot of attention from the business community and are very active areas of study and development. The considerable interest in those ideas is sparked by the substantial development potential in the manufacturing and automation industries, which has the potential to positively affect the lives of many people.

1.5 The Study's Objectives

1. To research how industrial predictive maintenance is expanding and developing 4.0.
2. Researching industry challenges is leading upkeep.
3. Researching a tool for displaying the patterns and dependencies in machine behavior.
4. To create a machine learning classifier that is data-driven and tailored to the Manufacturing sector.
5. To create a solid foundation for predictive analytics that anticipates machine health using cognitive techniques.
6. To create a thorough and general framework that could draw out information that might be used to support the activity of predictive maintenance from raw data.

1.6 The Study's Parameters

1. To comprehend the machine's manufacturing process for auto parts.
2. To make the best use of the limited resources at hand.
3. To choose elements that are pertinent to obtain effective outcomes with improved performance.
4. To use a machine learning technique that is appropriate and relevant to the data at hand.
5. To use machine learning to offer precise and timely findings that are solution oriented.

2 Literature Evaluations

Khin et al. suggested that manufacturers must embrace the digital transition toward Industry 4.0 because it boosts their flexibility, agility, and customer response (I4.0). The goal of this study is to identify the factors influencing the adoption of I4.0 by manufacturing organization's and to develop a triadic conceptual model to explain this phenomenon. This study's qualitative exploratory study methodology, which was based on several case studies (n = 15) from Malaysia's manufacturing sector, used in person interviews. The data were analyzed using NVivo. The conceptual model was developed using grounded theory and deductive thematic analysis. The findings demonstrate that driving, enabling, and hindering variables all have an impact on a firm's decision to embrace I4.0. The key influencing factors include anticipated benefits, market potential, labor concerns, consumer needs, competitiveness, and quality image. Additional barriers include finding the correct staff, a lack of resources, a lack of understanding, technical challenges, operator training, and altering operators' perspectives to accept new technology advancements. On the other side, enabling factors are those that involve resources, skills, and support. Due to its qualitative technique and limited sample size, this study's conclusions need to be supported by quantitative research to ensure that the proposed model may be more broadly used. Real-world implementations of the found I4.0 decision factors can be used to weigh advantages and disadvantages, explain advantages, identify skills and support that are needed, and highlight challenges to be prepared for. This will help manufacturers decide whether to invest in I4.0. Our research identifies critical ecosystem components that need to be developed as well as strategies for persuading manufacturers to use I4.0. The theoretical groundwork for a novel way to conceptualize I4.0 adoption outside of UTAUT is established by this study (Unified Theory of Acceptance and Use of Technology). It is easier to understand the factors that affect I4.0 adoption decisions when both positive and negative factors are taken into account [3].

Ouadah et al. shown that Predictive maintenance can use data from monitoring tools and process performance indicators to identify potential problems. Data from equipment monitoring is frequently utilized to train machine learning algorithms. The process of machine learning, which involves gathering and analyzing enormous amounts of data, aids in the improvement of computer accuracy. Machine learning methods most typically use supervised learning, in which labelled data is supplied into the system to train the algorithm. There are numerous supervised machine learning methods, though. It is therefore difficult to select the optimum supervised machine learning solution to deal with the problems of predictive maintenance. This research attempts to identify the best supervised machine learning strategy to improve the efficacy of predictive maintenance. We chose the top three algorithms for supervised machine learning Random forest, Decision tree, and KNN based on a comparison analysis of those methods. The effectiveness of the algorithms we had selected was then tested using real and made-up data sets. Finally, we conducted the experiment utilizing vibration analysis and dependability testing. We found that the efficacy of decision trees and random forests was pretty equal. When working with large datasets, KNN is the method of choice; however, random forests perform better when working with smaller datasets [4].

Keleko et al. shows the purpose of this essay is to investigate the issues with industrial maintenance, one of the major drivers of Ir 4.0 (I4.0), which has resulted in the appearance of new industrial barriers. Predictive maintenance 4.0 (PdM4.0) has made significant progress in this area and offers a number of potential advantages, such as an increase in productivity, especially by improving availability and quality, and cost savings through automated processes for production system monitoring, early failure detection, reduced machine downtime, and equipment life prediction. In order to provide practitioners and researchers with helpful guidance that may help them understand the key challenges and the most insightful scientific issues that characterize a successful application of Artificial Intelligence (AI) to PdM4.0, we focused our research on bibliometric analysis. Despite the fact that the bulk of them focus on the AI techniques used for PdM, the organization of predictive maintenance practices is not discussed in the papers that were used in this study. In order to evaluate and quantify the important concepts, application areas, approaches, and significant trends of AI applied to realtime predictive maintenance, our main contribution was to undertake a Bibliometric study utilizing the tools Biblioshiny, VOSviewer, and Power BI. As a result, we looked into the state of the research on these novel technologies today as well as their applications, associated methodology, and associated roles or effects in the development of I4.0. The final product lists the most well-known writers, organizations, publications, countries, and networks of author collaboration. As a result, American and Chinese institutes dominate the scientific discourse, and I4.0 and PdM4.0 publications are rapidly on the rise, particularly in the field of data-driven, hybrid models, and digital twin frameworks used for predictive diagnosis or anomaly detection. The development of PdM4.0 is significantly impacted by deep learning and similar developing fields. Then, we considered factors that can obstruct the successful implementation of AI-based systems in I4.0, including the data collection process, potential ethical implications, socioeconomic concerns, and transparency for all stakeholders. Finally, we presented I4.0 with our idea of a reliable AI [5].

Lmouatassime et al. Suggested that machine learning is a vital component in the environment of today. There are a lot of strategic benefits to using this technique, including assessing the equipment's condition and determining when repair is necessary. The new Sensors Reference Model (SRM) and Smart Maintenance Simulator (SmaSim) architecture suggested in this paper are based on an improved linked sensor known as Smart Sensors. Academics, engineers, and practitioners can select the top Smart Sensors and Machine Learning techniques for predictive maintenance in Smart Factory using this SmaSim [6].

Karrupusamy et al. suggested that predictive maintenance is a tool that may be used by any industrial company to enhance asset management. Working with the most expensive and advanced technology in the sector requires knowledge of predictive maintenance. The manufacturing sector is progressively using effective systems, routine maintenance procedures to keep track of the condition of business instruments. As a result of the digital transformation towards I4.0, data techniques, processes management, and communication networks, it is now possible to collect enormous amounts of operational and processes conditions information generated by numerous different pieces of equipment and harvest information for the development of an automatic fault detection and diagnosis system in order to reduce the amount of time and increase the utilization rate for the parts and increase their remaining useful life (I4.0). Effective property management in I40 requires proactive maintenance. This paper aims to provide a thorough review of recent advancements in metric capacity unit techniques widely applied to PdM for good production in I4.0 by classifying the analysis in accordance with metric capacity unit algorithms, ML category, industrial equipment and equipment used in data retrieval, categorization of wisdom size, kind, and highlight the key contributions of researchers. It also provides advice and hints. Random forest models were used in this study report to forecast the breakdown of diverse industrial machines. It reveals that, when compared to the Decision Tree (DT) technique, its accuracy and precision are superior [7].

Uloko et al. show that maintenance activities include corrective, preventative, and pdm. Our study emphasized monitoring systems, a kind of preventive maintenance for heavy truck brake pad failure. If an equipment breaks down, it can take months to obtain a replacement, leading to enormous losses in both moneys and life. Additionally, overly frequent maintenance could reduce output. This study looked at previously published research on the subject of maintenance forecasting. To our knowledge, Neural Networks have only ever been employed in machine learning techniques other than Neural Networks to predict brake pad failure. A large dataset and lots of processing power are needed for a neural network to make good predictions. It is crucial to evaluate the performance of the best supervised model when tackling a classification problem like this one from GitHub. We used Gaussian Nave Bayes, Decision Trees, and K-Nearest Neighbor to test the accuracy of our dataset. One set of the data was used for training and the other for testing; the training set had larger rows. The outcomes of the many iterations of the supervised algorithm we had selected were then compared. Python is a widely used programming language in this study. Based on the obtained results, we found that Decision Tree surpassed Gaussian Naive Bayes and K-Nearest Neighbor by 95%. Some of the index phrases are Gaussian Naive Bayes, Neural Network, K-Nearest Neighbor, and Decision Tree [8].

Schwendemann et al. show that it is crucial to minimize unplanned machine downtime on highly automated production lines that results from machine component failures. In machinery such as grinding machines, spinning components like bearings are essential. The detection of bearing failure has got significant research attention over the last ten years. Due to the expansion of ideas connected to machine learning, this topic has also gained more attention. There isn't a one-size-fits-all approach to predictive maintenance of bearings yet. So far, the majority of research have only examined one type of bearing at a time. An overview of the most important techniques for identifying bearing faults in grinding machines is given in this study. The analysis in this study is split into two parts. We'll start by looking at how bearing faults are categorized, including whether or not unfavorable conditions are to blame, where they occur (for example, on the inner or outer ring of the bearing), and how serious they are (based on how large the fault is). Predicting a component's remaining useful life before it breaks is essential for assessing its productivity prior to a failure, maximizing replacement costs, and minimizing downtime [9].

Al Mamlook et al. suggested that predictive maintenance is increasingly being used, which shows that it has distinct advantages over preventative maintenance. Even Nevertheless, Contemporary preventive maintenance techniques have substantial shortcomings in terms of enhancing reliability and maximizing maintenance. Machine learning has greatly outperformed many serious flaws of conventional maintenance prediction approaches during the last 2 decades. The special ability of machine learning to predict and optimize maintenance requirements is now being shown. In this study, a machine learning approach for use in predictive maintenance is provided that makes use of a number of classifiers. In order to identify the benefits and drawbacks of each preventive maintenance technique, researchers in this study compared the characteristics of novel approaches with those of more established ones. The author suggests additional research on how machine learning may enhance maintenance forecast and planning, boost equipment dependability, and produce the most potential benefit [10].

Ren et al. suggested that predictive maintenance, a proactive maintenance method, frequently performs better than corrective and preventative maintenance. However, reliability improvement and maintenance optimization are clearly constrained by conventional techniques to predictive maintenance. Over the previous two decades, machine learning significantly reduced the inherent faults of traditional maintenance prediction techniques. On the other hand, servicing forecasting and improvement using machine learning has demonstrated hitherto unheard of levels of accuracy. The elements of corrective, preventive, and predictive maintenance are contrasted in this study. The common predictive maintenance techniques are also evaluated, along with the advantages and disadvantages of each. This study then looks at driving dynamics and the advantages machine learning has over traditional maintenance methods. This article specifically discusses prevalent supervised learning and reinforcement learning techniques as well as their typical predictive maintenance applications. This report also summarises machine learning applications in maintenance prediction. The author concludes by presenting the following research on applying machine learning to improve maintenance forecast and planning, raise equipment dependability, and obtain the most possible advantage [11].

Sahli et al. show that Ir 4.0 has led to a significant technological advancement in industrial businesses all around the world (also known as Industry 4.0). By developing innovative production and product design processes, industrial automation and smart digital technologies can be coupled to produce smart products. Researchers have offered a variety of viewpoints on how the term “maintenance” has changed over the last several decades. The purpose of this article is to describe the evolution of industrial maintenance over time and to express an opinion on current industrial maintenance techniques related to Industry 4.0. The aim of this study is to pinpoint the challenges faced by industrial maintenance [12].

Banerjee et al. studied that the most recent paradigm shift in Industry 4.0 is the broad adoption of high-end industrial characteristics. Predictive maintenance, human comfort and safety standards, and an industrial Internet of Things (IoT) are all taken into consideration in the context of identifying abnormalities that could result in high expenditures due to downtime. Better process control is made possible by the Industrial Internet of Things (IIoT), a development in all networked systems. In today’s global economic and corporate environment, maintaining sophisticated engineering systems has emerged as a critical challenge for maximizing return on investment. This chapter discusses a number of studies related to the data-driven method of calculating the remaining usable life. It lists the different technical fields where the Internet of Things (IoT) can be applied. The Internet of Things (IoT) and cloud computing have made a variety of facilities possible around the globe [13].

Kalathas et al. suggested that every industry recognizes knowledge creation, which comes from the process of effective information, as a strategic asset and a source of competitive advantage. A significant amount of data is produced in the field of railroads, and it is important to review, best utilize, and use this data as a tool to help make decisions that will conserve resources and uphold the fundamental tenet of railroads, namely the safety of the passengers. This work makes use of data mining and machine learning approaches to create a train risk and control strategy using stored inactive data from a Greek railway company. We attempt to replace the antiquated corporate rolling stock maintenance methods with open source machine learning software called Weka (handwritten work orders from the supervisors to the technicians, dealing with the dysfunctions of a train unit by experience, the lack of planning and coding of the malfunctions and the maintenance schedule). With the aim of anticipating the diagnosis of the train fleet, the J48 and M5P algorithms from the Weka software are used to capture, process, and analyses data that can be used to monitor or find, with high accuracy, the prevention of probable damage or strains. The most recent methodology can be used as a tool to enhance the management of train performance in order to provide the data required for the execution of planning and the technical capability of the trains in order to achieve the most crucial objective for railroads, namely the safety of the passengers [14].

Kumar et al. show It's a new paradigm where intelligent devices are capable of working with humans to coordinate efficient production and distribution operations. Since the first industrial revolution began with the use of steam powered engines, industrial output has increased significantly up until the commencement of the fourth industrial revolution. Now that I4.0 has been introduced, industries will undergo a full transformation. This article includes an overview of previous studies' findings that analyses Industry 4.0's components and meaning. The purpose of this study article is to introduce the idea of I4.0, its drivers, and its components and to foster comprehension of them. A summary of the roles and actions performed by the government to encourage the use of technology and digitalization in manufacturing and production is also included in this document [15].

Nimawat et al. studied that most manufacturing firms in wealthy nations are converting to Industry 4.0 to maintain competitiveness. However, proper awareness of i4.0 should be required with regard to underdeveloped nations. This article presents the survey's results in order to assess how prepared Indian industrial sectors are to adopt Industry 4.0 advances. Additionally, through the establishment of hypotheses, readiness variables were validated based on the advantages that manufacturing industries experienced due to the use of Ir 4.0 technology. In addition, this survey is the first to look at the level of Industry 4.0 adoption in Indian industrial sectors. The results show that preparation criteria significantly influence the advantages brought about by the adoption of Industry 4.0, and a research agenda for the future is presented [16].

Pasi et al. show that the purpose of this article is to develop an ir 4.0 innovation ecosystem framework by looking at its essential components in order to ensure that the activities of many stakeholders are coordinated. Key viewpoints and their sub-components for the I4.0 innovation ecosystem framework were discovered by a thorough literature evaluation of articles from peer-reviewed journals in this research effort. Then, I4.0 issues among students and industries in higher education (HE) institutions in India are examined using questionnaire-based study design. The relevance of the detected perspectives, their sub-components, and causal linkages among components are then assessed using the decision making trial and assessment laboratory approach. The three points of view and their 45 sub points. I4.0 innovative ecosystem architecture components are identified from the literature review. The results demonstrate that both the government and HE institutions are directly impacted by the sector. While the government and industry have the largest effect on HE institutions. Limits and implications of the study in order to create the I4.0 innovation ecosystem framework, questionnaire results are analyzed. There are further approaches to developing ecosystem frameworks that go beyond the scope of this investigation. The government's ability to formulate policies will be aided by this research study. Additionally, it will aid managers in formulating plans for implementing I4.0 enabling technologies in their organizations. This researched report describes the creative ecosystem architecture for the successful adoption of I4.0 enabling technologies in Indian Manufacturing Industries [17].

Jena et al. suggested that in recent years, the Indian Manufacturing Sectors (IMI) have experienced fierce competition on the global market. The particular requirements of the customers determine and regulate the degree of uncertainty in the current market setting. Therefore, the manufacturing systems in the industries should be able to adapt to Industry 4.0's key elements and guiding principles, including versatility in parallelization, wide range, quickness, framework attentiveness and integration, auto data transfer with information exchange among manufacturing techniques, openness, and emotional intimacy. Therefore, if it wants to survive in the long run in the global market, it must adopt I4.0. However, only a small number of research work concerns are concerned in the issues caused by the adoption of Industry 4.0 in the manufacturing sector. This article's objective is to bridge the gap between the current Industrial System Requirements (ISR) and the barriers to I4.0 technology adoption in the established industries. The ISR and barriers were evaluated and analyzed using the data set acquired from a questionnaire-based survey. Fuzzy multi-criteria analysis is used to determine the most weighted SR and obstacles and to rank them in order of significance. It is also looked at how closely the two items correlate with one another. This study effort offers scholars, practitioners, and industrialists the ability to formulate MCDM issues while prioritizing the key barriers, system requirements, and them interdependencies through a range of case studies [18].

Ms. Midha et al. show that in practically every element of existence, the world is becoming more and more dependent on machines. Machine maintenance must advance along with the use of machinery, which is expanding. Predictive maintenance is a procedure used to keep an eye on machinery and equipment while it is in use to spot any faults or deteriorations and enable the necessary repair plan in advance, leading to lower operational costs and full tool and component utilization. Understanding the scope and sources of the literature on predictive maintenance systems is the primary objective of this bibliometric review paper. The Scopus database and data visualization software like Sciences cape provide the foundation for the bibliometric review. Given the increase in research into predictive maintenance during these years, the time series dataset under consideration spans from 2006 to May 12, 2021. A notable improvement was revealed in the articles on predictive maintenance, underscoring once more the value of paper reviews. This study offers some insightful analysis of the subject matter of current research in the area, as well as future directions and advancements [19].

Singh et al. suggested that Industry 4.0 could revolutionize operational productivity. Indian construction has lagged behind Industry 4.0. Project delays and departmental miscommunication owing to lack of real-time information reduce daily operations. To improve efficiency, India's construction industry must investigate Industry 4.0 adoption barriers. The literature research and expert talks identified 25 significant difficulties. Fuzzy TOPSIS, a multi-criterion decision-making (MCDM) technique, ranked the difficulties using uncertain and ambiguous inputs. Implementation and maintenance expenditures were the major hurdle, followed by finding qualified staff. Heavy layoffs, compensation changes, and legal impediments also impede Industry 4.0 adoption. This document should reveal important digital technology adoption barriers to enlighten management and aid decision-making [20].

Bisht et al. presented that the Indian industry can benefit from Industry 4.0. This article examines qualitative research methods and Industry 4.0 implementation strategies for Indian MSMEs from diverse sectors. The researchers interviewed and surveyed MSMES professionals. The snowball sampling approach was used to analyses India's industry 4.0 implementation challenges. Samples believe that authorities and educational institutions will provide a powerful implementation tool. The Knowledge Data Discovery (KDD) pipeline is used in this research to propose a technological framework for analyzing massive data in real-time and enabling quick decision making. The study is concluded with a framework for improving process data efficiency [21].

Jamwal et al. show that the Industry 4.0 has transformed global production. Industries are implementing Industry 4.0 business models to meet mass personalized wants and compete globally. Industry 4.0 is the data interchange and automation trend in production. In India, digitalization and Industry 4.0 are more popular than 4th industrial revolution. India lacks Industry 4.0research. However, India has implemented Industry 4.0 policies and technologies. This study aims to explain Industry 4.0 and related terminology. To propose Indian Industry 4.0 policies. Indian companies switching to Industry 4.0 b models should take Industry 4.0 practices seriously. Industry 4.0 implementation should address cyber security, machine-to-machine interaction, CPS dependability, and stability. This article discusses India's Industry 4.0 initiatives. High-investment and technology development initiatives in SMEs and MSMEs industry sectors are needed. Industry 4.0 infrastructure needs and industry preparedness. Industry 4.0 awareness campaigns [22].

Tiago et al. studied that "Industry 4.0," which involves cross-industry collaboration, is aiding technological change. Machines and managers must deal with massive data and customization while making production decisions. This problem is forecasting asset maintenance demand. Predictive maintenance decreases downtime, costs, and output control and quality. Industry 4.0 surveys and courses emphasize data analytics and machine learning to boost production, but not predictive maintenance and its structure. This article reviews predictive maintenance initiatives in Industry 4.0, including methodology, standards, and applications. This study discusses predictive maintenance restrictions and a new taxonomy for Industry 4.0. Due to the growing prominence of computer science areas like artificial intelligence and distributed computing in engineering, we decided a multidisciplinary approach was needed for Industry 4.0 [23].

Narula et al. define that Ir 4.0 factors are identified and categorized in this study. TheI4.0 factor pool for the literature is identified on this page. It discovers the crucial elements for Industry 4.0 in production, validates those using statistical techniques like factor analysis, principal component analysis, and item analysis, and then categorizes them. This study will shed light on key elements and supporting elements for deploying I4.0 in industrial sectors from the factor pool. This study will shed light on I4.0's application in the manufacturing sector. I4.0 is transformed through strategy, leadership, and culture. Manufacturing companies have taken into account simulations, virtual testing, and digital twin design. The construction of the manufacturing I4.0 roadmap, readiness index, and strategy will all start with the suggested I4.0 factor stratification model. In order to help policymakers, researchers, academics, and practitioners implement Industry 4.0, this article identifies and validates I4.0 criteria. The foundation for a manufacturing I4.0 maturity model is laid forth in this study. A factor pool is developed after a thorough analysis of the I4.0 literature, which is then submitted to experts to ensure accuracy and thoroughness, particularly for sub-factors related to manufacturing. Significant I4.0 factors are identified and confirmed in this investigation [24].

Chazhoor et al. show that for semiconductor devices, forecasting is simpler to do than preventative and breakdown maintenance. This study uses a dataset from the Semiconductor Manufacturing process to test machine learning predictive models (SECOM). Signals from semiconductor devices and statistics about semiconductor manufacturing are included in the collection. Data pre-processing, which is a crucial step in applying many machine learning methods, is challenging with the SECOM dataset due to its high complexity and class imbalance issue. Based on performance metrics including accuracy and the Receiver Operating Characteristic (ROC) curve, numerous predictive effective classification models were compared and compared. Devices; thus overall leads the efficiency to be increased in manufacturing [3]. Maintenance is one of the manufacturing areas that Industry 4.0 is introducing the use of computers and digitalization in [4, 5] and prognostics and health management (PHM) has become an obvious for smart industrial evolution; moreover, it provides a dependable solution for managing the health state of industrial equipment. Maintenance is vital since it extends the lifetime of an equipment. A system's lifespan can be prolonged by implementing maintenance. Maintenance should be scheduled ahead of time with a precise prediction of the machine failure for avoiding the accidents in production line and to reduce the economic loss. Predictive Maintenance (PdM) is widely employed in a variety of industries, including manufacturing [6, 7], car [8], and aerospace [9]. Engineering tools working well in anticipating the failure time of equipment in advance. Furthermore, PdM is supposed to foresees the failure precisely [10, 11]. Data flexibility is viewed by PdM as a significant concern that could impair algorithm performance for data driven modelling [12]. Processing raw sensor data provides additional problem since sensor data is not labelled. Furthermore, while addressing the problem of data tagging, data sparsity may impair algorithm performance in existing methodologies. Furthermore, it is frequently difficult to discover abnormalities and trends in high-dimensional IoT data [13]. It is considerably more difficult in large data situations because of raw data [14]. However, data-driven AI systems helps in PdM by using the IoT sensor collected data [15–17]. This research is to create a PdM system which uses machine learning practices to generate accurate forecasts of future faults for industrial production lines before they occur. Novel methods were examined using a real-time data collected through sensors for an automobile part making machine to find best model to solve this challenge [25].

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