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Improving Predictive Maintenance in Industrial Machines through Machine Learning and Real-Time Monitoring

Gajanan Ankatwar*
Ph.D., Scholar, Datta Meghe Institute of Higher Education and Research,
Sawangi(Meghe), Wardha, Maharastra, India.
*Corresponding Author: ankatwar.gajanan@gmail.com.

Dr. Chitra Dhawale
Research Supervisor, Professor & Head. Faculty of Science and Technology,
Datta Meghe Institute of Higher Education and Research,
Sawangi(Meghe), Wardha, Maharastra, India

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ABSTRACT

In recent years, the fourth industrial revolution has garnered global interest. This new revolution has given rise to numerous concepts, one of which is predictive maintenance. By implementing machine-learning techniques to monitor real-time operational data, predictive maintenance can be achieved for industrial machines. It analyzes sensor data to predict equipment failures early and reduce downtime, ultimately optimizing scheduled maintenance. The aim of this study was to investigate the advancements in academic failure prediction. Predicting failures requires considering concepts like design support systems and predictive maintenance decision support systems. The research gap was identified by reviewing the existing literature and exploring optimization strategies through the integration of predictive maintenance in the industrial environment of smart factories.

Introduction

Predictive maintenance, often referred to as "condition-based maintenance," "on-line monitoring," or "risk-based maintenance," has a long history and has been the subject of numerous current projects. This technique involves proactive machinery monitoring to prevent future problems. From the initial visual inspection method to automated systems utilizing advanced signal processing technologies such as machine learning, pattern recognition, fuzzy logic, and neural networks, predictive maintenance has come a long way. Automated technology is a viable solution in many fields when human senses are no longer able to detect and receive crucial information from equipment, particularly motors [7].

Predictive maintenance, when combined with integrated sensors, can significantly reduce the need for unnecessary equipment replacements, minimize machine downtime, identify the source of the problem, and ultimately reduce costs while boosting productivity. To achieve this, preventive maintenance (PdM) and scheduled maintenance (SM) work together to schedule maintenance tasks in advance to avoid machine breakdowns. Unlike traditional preventative maintenance, PdM programs rely on data gathered from sensors and analysis techniques [8, 9]. Over 70% of the driven electrical loads in the manufacturing sector use induction motors [10]. Several studies have been conducted in this field to better assess the fitness of these motors. The most common repair issue and the most frequent cause of motor failure are bearing failures [10].

In recent years, the importance of system maintenance has increased for enhancing the continuity and productivity of products. System maintenance can take various forms, including proactive, planned, reactive, and predictive maintenance [11]. Reactive maintenance only deals with issues that arise when a system fails or breaks down. Once the fault is identified, the necessary repairs are made. Conversely, planned maintenance is intended to conduct regular inspections and maintenance tasks at predetermined intervals to extend the system's life and lower repair costs. Predictive maintenance (PdM) aims to maximize maintenance intervals, decrease downtime, and increase system reliability by using advanced analytics to evaluate data from multiple sensors and predict when a system is likely to fail.

PdM has advanced significantly in recent years due to the development of low-cost sensors and real-time monitoring systems that have enabled the collection of big data. These advances, combined with skilled algorithms and human expertise, have contributed to significant advancements in PdM.

New multivariate statistical models and expert algorithms are currently being developed to reduce labor costs and increase prediction accuracy [12]. Advanced models, algorithms, and expertise based on AI enable robotic systems to achieve greater autonomy. Moreover, AI-based PdM can lower costs while increasing effectiveness and security. Therefore, researchers have primarily focused on AI theories and methods to enhance the adaptability and autonomy of robotic systems in complex and dynamic industrial scenarios [13].

The Prognostics and Health Management (PHM) system uses a combination of unsupervised and supervised learning techniques, including total AI methods, clustering, reinforcement learning, and classification/regression to process the large amounts of data collected through real-time condition monitoring. The implementation of Deep Neural Networks (DNNs) covering Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs) has improved the reliability of predictions in the PHM system. These networks are trained on raw sensor data, such as images or time-series data, to identify, detect, or predict variations in a system.

Various PHM applications have successfully implemented machine learning (ML) methods, such as Support Vector Machines (SVMs), Random Forests (RF), decision trees (DT), and feedforward neural networks (FNNs) for classifying sensor data. To improve data quality, data-cleaning techniques can be used to handle missing values and efficiently remove noise. Efficient data management through secure and reliable communication can also improve performance.

There are several fields in which computer-based technology is combined with human-centered approaches, including decision algorithms, electric automobiles, electric control, power, and energy, predictive analysis, and cellular and security networks. Some examples of literature in these fields are decision algorithms [18-22], electric automobiles [23-24], electric control, power, and energy [24-28], predictive analysis [29-31], and cellular and security networks [32-36].

Literature Review

The use of condition monitoring and Predictive Maintenance (PdM) can significantly increase system dependability and prevent financial losses from unplanned motor failures, particularly for electric motors and other types of equipment. This research proposes an RF-based ML framework for PdM, which was evaluated in an actual industrial scenario using a machine learning approach for data collection and analysis, and compared to the evaluation of a simulation tool. The Azure Cloud Architecture's Analysis of Data Tool gathers data from several sensors, PLCs in the machine, and communication channels, and the results showed the correct behavior of the approach in predicting different machine states.

Machine learning (ML) is a revolutionary technique with applications in various fields, including autonomics, production and manufacturing, image processing, medicine, and aviation. An automated monitoring system and routine maintenance are crucial for the smooth operation of a machine. Our goal is to address the deficiency of an automation system that provides the accuracy rate of a manufacturing machine at a specific moment in time, as well as the lack of recording of crucial energy meter values needed to generate a power report at a specific period in an automation system to handle production concerns. In this study, we explain how ML approaches are applied to forecast the precision of an operational production machine. We employed supervised ML for binary decision trees using the CART method and retrieved data through the Modbus communication protocol using an RS232 to RS485 converter for the power report.

The use of Internet of Things (IoT) technology in industrial settings to gather valuable information by analyzing data collected from various sensors is known as Industrial Internet of Things (IIoT). Predictive modeling requires a date-time element, which is commonly included in the data gathered by machines [3]. This study examines the application of ARIMA prediction using time-series data from multiple sensors on a slitting machine to identify potential failures and quality issues in order to improve the manufacturing process as a whole. Machine learning (ML) is a crucial component of IIoT and has applications in quality control and management, maintenance cost reduction, and industrial process optimization.

In highly automated production processes, minimizing unplanned machine downtime due to faulty machine components is crucial. Bearings inside machine tools, such as grinding machines, are vital components. Research on bearing defect detection has increased significantly over the past decade [4]. The success of ML concepts has also contributed to the increased interest in this topic. However, there is currently no single, widely applicable technique for predictive bearing maintenance. Most research has only focused on one type of bearing at a time. This study provides an overview of the main techniques for evaluating bearing defects in grinding machines, highlighting two main aspects of the analysis.

The widespread adoption of Industry 4.0 has led to the increased use of Predictive Maintenance (PdM) techniques, smart systems, and machine learning in artificial intelligence (AI) across various industries. These methods aim to optimize the performance of industrial equipment by minimizing downtime and enhancing the utilization of its components. The digital transformation towards Industry 4.0 has enabled the collection of vast amounts of operational and process condition data from multiple pieces of equipment, which can be used to develop automated fault detection systems that help to extend the life of these components.

In recent years, there has been a growing interest in the application of PdM in smart manufacturing in Industry 4.0, and machine learning approaches have shown significant promise. The implementation of PdM can benefit every industrial industry by enhancing asset management and ensuring the optimal performance of expensive and sophisticated machinery. In the manufacturing sector, businesses are increasingly adopting good systems, PdM, routine maintenance procedures, and machine learning approaches to maintain the condition of their equipment.

The collection of large volumes of operational and process condition data from multiple pieces of equipment can be used to develop an automatic fault detection system that can determine how to reduce the time it takes for a fault to occur, increase the rate at which a part is utilized, and extend its useful life. The properties of Industry 4.0 that generate products require PdM to ensure sustainable smart manufacturing.

Research Methodology

The following sentence has been rephrased to improve its language quality and clarity while maintaining its original meaning:

The PdM data is collected and saved in a time series from the IoT cloud. There are two ways in which the data is stored:

Primary Storage: The data is stored in an online IoT cloud data lake, where it has been preprocessed and analyzed using the available information.

Backup Record: A freely accessible csv-formatted dataset from Kaggle was utilized for data analysis and ML model development.

To ensure secure data transfer, the IoT cloud provides a reliable communication route. After the collection of prediction maintenance data from the IoT cloud, data processing can be performed to handle missing data and noise. Data transformation is carried out by normalizing and standardizing the data values to enhance the performance of the model. This is followed by supervised learning using machine learning techniques such as RF, SVM, KNN, and decision tree.

Data cleaning is necessary to remove unwanted or unnecessary items from the raw data. This is achieved through techniques such as outlier identification to control the ingestion of noisy values and missing data.

During data transformation, data normalization is performed to scale the data values into the desired range, and new attributes are created from known attributes.

Finally, data processing is carried out using ML techniques, with values such as pressure, volume, and temperature used to predict the data using RF, SVM, and decision trees.

The PdM system is built upon four main components: a user interface screen, industrial machinery, an IoT cloud for storage, and a Thing-speaking interface. The edge device collected data from the industrial machine, which was then stored in the Thing Speech Cloud Analytic Platform in a time-series format. If there were issues with online connectivity, a local dataset from Kaggle was used. Programming of edge devices was done using libraries such as Flask, Scikit-Learn, and Python 3.6. The system collected data from the industrial machine using the UCI ML Repository, and the model development section used this data to train and process the data using ML algorithms, including K-nearest neighbors, RF, SVM, and decision tree. The system uses predictive analysis to address the maintenance schedule and behavior of the industrial machine. By collecting data on pressures, vibrations, temperatures, power usage, and other factors, the system can be continuously evaluated. Several algorithms, including RF algorithms, were applied to the collected data to predict the failure phase of equipment. To achieve high accuracy, the system handles outliers, missing values, and performs data cleaning. Feature selection and hyperparameter fine-tuning are used to optimize model performance, which should be continuously monitored using updated data.

TABLE I. ACCURACY OF ML MODELS

Model	Accuracy
Random Forest (RF)	0.92
Support Vector Machines (SVM)	0.76
Decision Trees(DT)	0.85
K-nearest neighbours	0.88

Results

The model development section utilizes machine learning (ML) algorithms, including K-nearest neighbors, random forest (RF), Support Vector Machines (SVM), and Decision Trees, to process and train data from the IOT cloud. The user interface panel displays predicted results, simplifying the employment of predictive analysis to optimize system behavior and maintenance plans. By employing RF algorithms and other techniques, it is possible to predict failure phases based on variations in data features, such as vibration and volume. These predictions are made possible by the continuous evaluation of parameters, including pressure, vibration, temperature, and power consumption. The accuracy of the ML models is demonstrated in Table I and Fig.1.

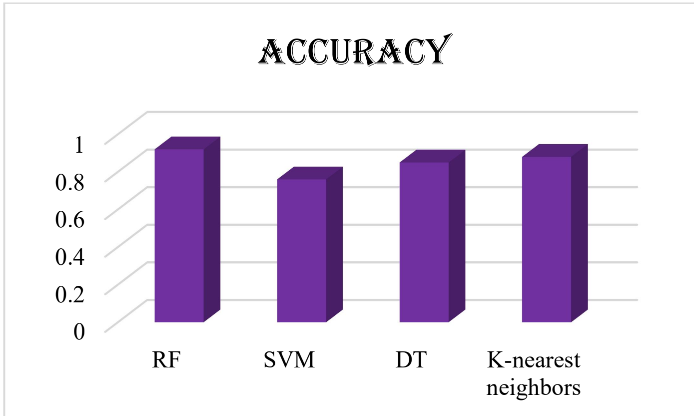

Fig. 1. Accuracy of ML Models

Table II and Fig. 2 showcase the accuracies of the machine learning models. Table III and Fig. 3 present the recall of the models. Precision refers to the proportion of correctly predicted positive instances out of all the instances that the model predicted to be positive. On the other hand, recall represents the percentage of genuine positive cases that the model accurately identified. This metric is useful in evaluating a model's performance, which is calculated as the harmonic mean of precision and recall.

TABLE II. PRECISION OF ML MODELS

Model	Accuracy
Random Forest	0.91
SVM	0.87
DT	0.83
K-nearest neighbors	0.86

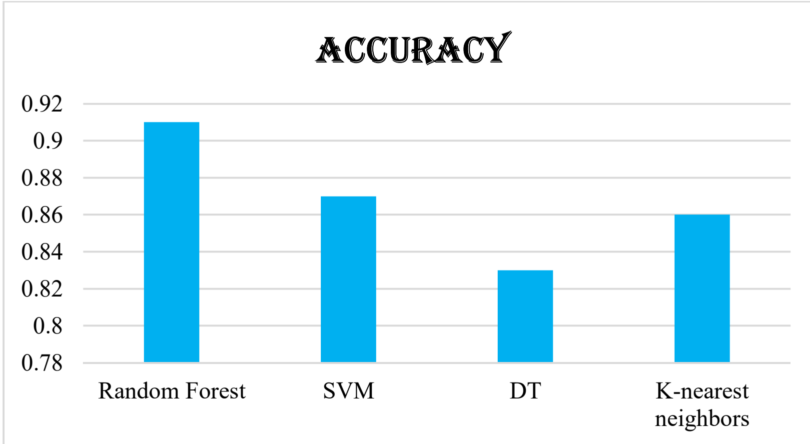

Fig. 2. Precision of ML Models

TABLE III. RECALL OF ML MODELS

Model	Accuracy
Random Forest	0.93
SVM	0.90
DT	0.86
K-nearest neighbors	0.89

Predictive maintenance can be effectively deployed in connected product environments and smart factory settings, providing a variety of benefits, including reduced occurrence of unplanned breakdowns, extended asset uptime, improved asset reliability, and decreased operational expenses through proactive maintenance and field service activities. The F1 scores, confusion matrices for random forest, SVM, decision tree, and KNN models are provided in Tables IV to VII, and the ROC-AUC scores are listed in Table IX. Additionally, the mean absolute error for the ML model is presented in Tables IX and X.

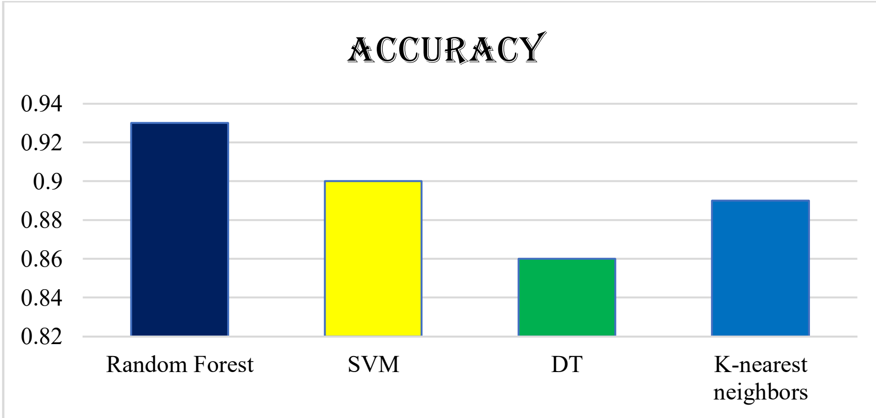

Fig. 3. Recall of ML Models

TABLE IV. F1-SCORE OF ML MODELS

Model	Accuracy
RF	0.92
SVM	0.88
Decision Tree	0.84
K-nearest neighbors	0.87

TABLE V. CONFUSION MATRIX FOR RANDOM FOREST

	Predicted: No Failure	Predicted: Failure
Actual: No Failure	480	20
Actual: Failure	30	470

TABLE VI. CONFUSION MATRIX FOR SUPPORT VECTOR MACHINE

	Predicted: No Failure	Predicted: Failure
Actual: No Failure	470	30
Actual: Failure	40	460

TABLE VII. CONFUSION MATRIX FOR DECISION TREE

	Predicted: No Failure	**Predicted: Failure**
Actual: No Failure	450	50
Actual: Failure	60	440

TABLE VIII. CONFUSION MATRIX FOR K-NEAREST NEIGHBORS

	Predicted: No Failure	**Predicted: Failure**
Actual: No Failure	460	40
Actual: Failure	50	450

TABLE IX. ROC-AUC SCORE FOR ML MODELS

Model	**ROC - AUC**
Random Forest	0.95
SVM	0.92
DT	0.88
K-nearest neighbors	0.91

TABLE X. MEAN ABSOLUTE ERROR (MAE) OF ML MODELS

Model	**MAE**
Random Forest	0.07
SVM	0.09
DT	0.11
K-nearest neighbors	0.08

Discussion

The datasets from each publication that were examined were vital for designing a solution for this problem. In order to train an AI model successfully, it is necessary to have data that meets both qualitative and quantitative requirements. Specifically, a substantial amount of high-quality data is needed for the model to perform well. This information pertains to the PdM and the operation of the device. This function can involve both error-prone and error-free activities, or it can involve only the data that result from errors. In the first scenario, there is a large amount of data available, assuming that numerous operational situations have been recorded. However, the second requirement is data quality. When a machine is functioning properly, it operates smoothly. There will be a substantial amount of data from regular operation and only a small amount of data from faults when an error occurs and is logged, which can cause many issues during training. This issue, known as "unbalanced data," frequently arises when datasets are obtained from real-world problems.

Typically, a class with adverse circumstances is considered the one under examination if it is not numerically superior. When the prediction model is running, four states are generated. Both correct and incorrect procedures have two scenarios in which the forecast is accurate. The other two scenarios are instances where the forecast proves to be ineffective.

There are various methods to address this issue, with the most commonly used being the recalibration of a sample. Three techniques are employed: oversampling, subsampling, and their combination. Subsampling is typically used in the dominant class to reduce size, while techniques such as data synthesis or duplicate data are utilized in the less powerful class.

In addition, sensors serve as the medium through which data is produced. They collect a multitude of measures and combine them at various points, as previously mentioned.

The accuracy of these sensors is crucial because the model's training and accurate predictions depend on the data they provide. Due to technological advancements, small sensors can now be easily fitted to almost any type of construction. Additionally, today's measurements are highly accurate, resulting in reliable data for building the model. As technology continues to advance, sensors will become even more accurate and smaller, leading to more sensors and more effective models. Artificial intelligence has made significant progress in recent years, with high-performance models being developed in conjunction with increasing data accessibility. One of the main challenges is that the machine learning models used were viewed as "black boxes." Consequently, there is insufficient justification for why a system should be shut down for maintenance. Future work will focus on overcoming this obstacle. After some success has been achieved, there will be a larger push to apply machine learning methods in predictive maintenance (PdM). Furthermore, the current trend is on the rise.

Challenges

One of the main criticisms of most machine learning (ML) approaches is their black-box nature, which makes it difficult to obtain a precise mathematical description for most ML and deep learning (DL) techniques. A significant maintenance issue with ML methods is their pessimistic nature, which can be problematic when trying to understand why a specific forecast was made. While classification accuracy is a useful metric, it is not always sufficient to fully describe real-world jobs.

When it comes to predictive modelling, it is important to understand not just what is expected, but also why a particular forecast was made. In some cases, a low-risk environment may be sufficient to view the forecast results alone, rather than the explain ability of the results. However, in other situations, the explain ability of the models is crucial for gaining a more precise understanding of the problem and data. The demand for explain ability arises when there is insufficient problem elucidation, as the forecast findings only partially resolve the problems.

There are certain requirements for interpretability and explain ability, such as human cognition and education. People are generally interested in learning and discovering meanings, so candidates who receive a low prediction accuracy or are rejected by a certain ML model may be deemed unacceptable or unsatisfactory. Additionally, explain ability and interpretability draw on additional knowledge that the model has learned, which is important in scientific knowledge and learning.

Finally, safety precautions are also a concern when it comes to complex task structures. It is difficult to imagine all situations in which a complex task structure can collapse, and it is not mathematically possible to list every input and output. Therefore, it is important to ensure that models are explainable and interpretable in order to mitigate potential safety risks.

An AI model that is explainable will also be fair, as it generates unbiased predictions and safeguards data privacy. It is reliable because small input variations do not significantly impact the outputs, and it is trustworthy because people are more likely to trust explainable models over complex, opaque models. Human feedback enhances both the data and the model due to the clear outcomes, resulting in more accurate predictions.

Interpretability and explain ability are often used interchangeably in ML and AI systems. Explain ability pertains to the extent to which a complex ML model's inner workings are comprehensible to humans, while interpretability refers to the ability to forecast the outcome of altering a model's input variables.

Employing algorithms that generate interpretable models is the most straightforward method for achieving interpretability. Some of the most common interpretable models include decision trees [38], decision rules [39], and logistic regression [39].

Conclusions

Not only is machine learning (ML) currently dominating the field of robotics, but it is also advancing at a rapid pace in the manufacturing industry's industrial and production sectors. Automation with high-quality output is becoming a reality as ML approaches are being adopted and implemented. The primary goal of this research is to implement a method for estimating the accuracy of manufacturing machines and to increase the output quantity, quality, and lifespan. Additionally, the article aims to present a cutting-edge approach in the field of ML-assisted automation of industrial machinery.

Predictive maintenance (PdM) solutions are designed to support the evaluation of equipment to determine when repairs are necessary. This approach offers lower costs than routine or time-based PdM because actions are only taken when necessary. As a result, it is considered condition-based maintenance carried out in line with the assessments of the level of deterioration of an object. The key advantages of PdM include the ability to schedule corrective maintenance conveniently and protect equipment from unplanned breakdowns. Some encouraging results of PdM include reduced machine downtime, avoided unnecessary maintenance costs, and increased revenue streams for equipment suppliers that provide aftermarket services. However, when integrating PdM technology into their organizations' operations, scientists and engineers face challenges related to data and processes. This work can be expanded to include neural networking and its applications.

The most commonly used techniques for predictive maintenance (PdM) are reported to be RF, SVM, and ANN, but the effectiveness of these approaches depends on the specific data related to the problem at hand. In addition, PdM applications typically utilize multiple sensors to acquire a wide range of data, which is a common requirement for these operations. Among the 12 types of sensors, noise, temperature, sound, and vibration sensors are the most frequently used in PdM applications involving machine learning.

These findings point to the importance of including temperature, vibration, and noise as key parameters in PdM ML models. Future research could focus on sector-specific PdM studies to evaluate the performance of these models in specific industries and to gain further insights. Additionally, connecting sensors to specific sectors could highlight the specific sensors used. Overall, a review of available data and current efforts to address the issue of black box models suggests that the adoption of PdM is expected to grow rapidly in the coming years, with many businesses in the production sector investing in this technology.

Future Study

Machine learning (ML) techniques have shown significant success in industrial maintenance but face two major issues: their "black-box" nature, hindering interpretability, and limited generalization. To tackle the challenge of understanding system decisions, Explainable Artificial Intelligence (XAI) has emerged, aiming to enhance ML model interpretability while maintaining high predictive accuracy. Mechanical problems can cause costly production delays. By employing XAI in maintenance, downtime impact can be reduced, and performance monitoring can be improved, anticipating and resolving issues proactively. XAI can identify patterns in maintenance data, enabling more efficient scheduling and decreasing unexpected downtime. XAI also fosters trust with clients by improving system interpretability and advancing the technology. XAI ensures that systems operate with high accuracy, integrity, and performance, adhering to ethical and professional standards.

References

[1] M. Paolanti, L. Romeo, A. Felicetti, A. Mancini, E. Frontoni, and J. Loncarski, "Machine learning approach for predictive maintenance in industry 4.0," in *2018 14th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA)*, 2018, pp. 1-6.

[2] K. I. Masani, P. Oza, and S. Agrawal, "Predictive maintenance and monitoring of industrial machine using machine learning," *Scalable Computing: Practice and Experience*, vol. 20, no. 4, pp. 663-668, 2019.

[3] A. Kanawaday and A. Sane, "Machine learning for predictive maintenance of industrial machines using IoT sensor data," in *2017 8th IEEE International Conference on Software Engineering and Service Science (ICSESS)*, 2017, pp. 87-90.

[4] S. Schwendemann, Z. Amjad, and A. Sikora, "A survey of machine-learning techniques for condition monitoring and predictive maintenance of bearings in grinding machines," *Computers in Industry*, vol. 125, p. 103380, 2021.

[5] Z. M. Çınar, A. Abdussalam Nuhu, Q. Zeeshan, O. Korhan, M. Asmael, and B. Safaei, "Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0," *Sustainability*, vol. 12, no. 19, p. 8211, 2020.

[6] P. Karuppusamy, "Machine learning approach to predictive maintenance in manufacturing industry-a comparative study," *Journal of Soft Computing Paradigm (JSCP)*, vol. 2, no. 4, pp. 246-255, 2020.

[7] H. M. Hashemian, "State-of-the-art predictive maintenance techniques," *IEEE Transactions on Instrumentation and Measurement*, vol. 60, no. 1, pp. 226-236, 2010.

[8] S. J. Wu, N. Gebraeel, M. A. Lawley, and Y. Yih, "A neural network integrated decision support system for condition-based optimal predictive maintenance policy," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 37, no. 2, pp. 226-236, 2007.

[9] E. Frontoni, R. Pollini, P. Russo, P. Zingaretti, and G. Cerri, "HDOMO: Smart sensor integration for an active and independent longevity of the elderly," *Sensors*, vol. 17, no. 11, p. 2610, 2017.

[10] B. Lu, D. B. Durocher, and P. Stemper, "Predictive maintenance techniques," *IEEE Industry Applications Magazine*, vol. 15, no. 6, pp. 52-60, 2009.

[11] J. Dalzochio et al., "Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status and challenges," *Computers in Industry*, vol. 123, p. 103298, 2020.

[12] M. R. Khatri, "Integration of natural language processing, self-service platforms, predictive maintenance, and prescriptive analytics for cost reduction, personalization, and real-time insights customer service and operational efficiency," *International Journal of Information and Cybersecurity*, vol. 7, no. 9, pp. 1-30, 2023.

[13] Y. Ren, "Optimizing predictive maintenance with machine learning for reliability improvement," *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering*, vol. 7, no. 3, p. 030801, 2021.

[14] A. Shamayleh, M. Awad, and J. Farhat, "IoT based predictive maintenance management of medical equipment," *Journal of Medical Systems*, vol. 44, no. 4, p. 72, 2020.

[15] H. A. Gohel, H. Upadhyay, L. Lagos, K. Cooper, and A. Sanzetenea, "Predictive maintenance architecture development for nuclear infrastructure using machine learning," *Nuclear Engineering and Technology*, vol. 52, no. 7, pp. 1436-1442, 2020.

[16] C. Gianoglio, E. Ragusa, P. Gastaldo, F. Gallesi, and F. Guastavino, "Online predictive maintenance monitoring adopting convolutional neural networks," *Energies*, vol. 14, no. 15, p. 4711, 2021.

[17] M. Pech, J. Vrchota, and J. Bednář, "Predictive maintenance and intelligent sensors in smart factory," *Sensors*, vol. 21, no. 4, p. 1470, 2021.

[18] B. P. Joshi, "Some generalized intuitionistic fuzzy geometric aggregation operators with applications in multi-criteria decision making process," Intelligent Systems: Concepts, Methodologies, Tools, and Applications. pp. 1190–1211, 2018. doi: 10.4018/978-1-5225-5643-5.ch050.

[19] B. P. Joshi and A. Kumar, "New Einstein Hybrid Aggregation Operators for Intuitionistic Fuzzy Sets and Applications in Multi-Criteria Decision-Making," pp. 252–283, 2018, doi: 10.4018/978-1-5225-5709-8.ch012.

[20] R. Kamra et al., "Sustainability of Renewable-Energy-Sources-Classification utilizing Moderator-Intuitionistic-Fuzzy Hybrid Averaging Operator," in ICAECT, IEEE, Jan. 2024, pp. 1–5. doi: 10.1109/ICAECT60202.2024.10469098.

[21] B. P. Joshi and A. Singh, "Multi-Criteria Decision-Making Approach Based on Moderator Intuitionistic Fuzzy Hybrid Aggregation Operators," pp. 237–251, 2018, doi: 10.4018/978-1-5225-5709-8.ch011.

[22] A. Kumar et al., "Opportunities and Challenges for Electric Vehicle Wireless Charging with Home," in PEEIC, IEEE, Dec. 2024, pp. 221–225. doi: 10.1109/peeic59336.2023.10451967.

[23] Sagar, et al., "A Self-Improved Optimization-Based Artificial Neural Network Model for WPT System for Electric Vehicle Charging," in PEEIC, IEEE, Dec. 2024, pp. 156–163. doi: 10.1109/peeic59336.2023.10450276.

[24] Singh, B. P. Joshi, and B. K. Singh, "Linear Quadratic Control Scheme for Isolated and Inter-connected Power System," in ICACITE 2023, pp. 1913–1916, 2023, doi: 10.1109/ICACITE57410.2023.10182601.

[25] N. Kumar, H. Malik, A. Singh, M. A. Alotaibi, and M. E. Nassar, "Novel Neural Network-Based Load Frequency Control Scheme: A Case Study of Restructured Power System," IEEE Access, vol. 9, pp. 162231–162242, 2021, doi: 10.1109/ACCESS.2021.3133360.

[26] P. Garia, A. Mittal, A. Singh, N. Kumar, and S. Oli, "A Study and Performance Review of an On-Grid PV Solar Plant Using Artificial Intelligence," in PEEIC, IEEE, Dec. 2023, pp. 484–489. doi: 10.1109/PEEIC59336.2023.10451368.

[27] M. M. Sati et al., "Ambiguous Fuzzy Einstein Geometric Operator: Utilizing to Analyze Power Generation Techniques," in ICDT, IEEE, Mar. 2024, pp. 1536–1541. doi: 10.1109/ICDT61202.2024.10488926.

[28] S. Rathee, A. Mittal, N. Kumar, and A. Singh, "Assessment of Two 20Kw PV Solar Energy Generation Plants in Homogeneous Environments," in PEEIC, IEEE, Dec. 2023, pp. 449–455. doi: 10.1109/PEEIC59336.2023.10451686.

[29] B. P. Joshi et al., "MIFS Ordered Weighted Operators method for renewable-energy-source-selection," 2023 IEEE 2nd Int. Conf. Ind. Electron. Dev. Appl., pp. 248–253, 2023, doi: 10.1109/icidea59866.2023.10295267.

[30] S. Sharma et al., "Predictive Model for Dissolved Oxygen in water body (Nainital Lake) of Nainital district by Multivariate Regression Analysis," in ICACITE, IEEE, May 2023, pp. 376–379. doi: 10.1109/icacite57410.2023.10183174.

[31] A. Mittal at al., "The Nexus Among Use of Sustainable Energy Sources and CO2 Releases," ICACITE 2023, pp. 734–738, 2023, doi: 10.1109/ICACITE57410.2023.10182905.

[32] B. P. Joshi, M. Pandey, and S. Kumar, Use of intuitionistic fuzzy time series in forecasting enrollments to an academic institution, vol. 436. 2016. doi: 10.1007/978-981-10-0448-3_70.

[33] S. Sharma et al., "Forecasting of Carbon Emissions in India Using (ARIMA) Time Series Predicting Approach," Lect. Notes Electr. Eng., vol. 1086, pp. 799–811, 2024, doi: 10.1007/978-981-99-6749-0_53.

[34] S. Oli et al., "Real Time Railway Security System using Sensor Network," in INCOFT, IEEE, Nov. 2023, pp. 1–4. doi: 10.1109/INCOFT60753.2023.10425570.

[35] M. Manu et al., "Exploring the Effects of Size and Shape on the Melting Temperature of CdS Nano Semiconductors," in ICACITE 2023, IEEE, May 2023, pp. 1945–1949. doi: 10.1109/ICACITE57410.2023.10183007.

[36] V. Vimal et al., "Artificial intelligence-based novel scheme for location area planning in cellular networks," Comput. Intell., vol. 37, no. 3, pp. 1338–1354, 2021.

[37] V. Vimal et al., "Enhance Software-Defined Network Security with IoT for Strengthen the Encryption of Information Access Control," Comput. Intell. Neurosci., 2022.

[38] C. Kingsford and S. L. Salzberg, "What are decision trees?," *Nature Biotechnology*, vol. 26, no. 9, pp. 1011-1013, 2008.

[39] C. Apté and S. Weiss, "Data mining with decision trees and decision rules," *Future Generation Computer Systems*, vol. 13, no. 2-3, pp. 197-210, 1997.