NEWPORT INTERNATIONAL JOURNAL OF SCIENTIFIC AND EXPERIMENTAL SCIENCES (NIJSES)

Volume 6 Issue 3 Page 7-13, 2025

©NIJSES PUBLICATIONS
Open Access

ONLINE ISSN:2992-5819
PRINT ISSN:2992-6149

https://doi.org/10.59298/NIJSES/2025/63.713

Artificial Intelligence in Predictive Maintenance for Industry

Awafung Emmanuel

Electronics and Biomedical Engineering, Kampala International University Uganda

Email: awafungadie@gmail.com

ABSTRACT

Artificial Intelligence (AI) has emerged as a transformative force in the realm of industrial predictive maintenance (PdM), enabling businesses to anticipate equipment failures and optimize maintenance schedules. This paper examines the integration of AI technologies such as machine learning, deep learning, and IoT systems into predictive maintenance frameworks. Drawing on case studies and current implementations across various sectors, including manufacturing, steel production, and ICT infrastructure, the research examines key processes such as data acquisition, preprocessing, model development, and decision-making. It also evaluates the use of advanced sensors and wireless networks, the architecture of predictive models, and practical implementation strategies. Benefits, including reduced operational costs, minimized downtime, and enhanced safety, are discussed alongside challenges such as data quality, model accuracy, and organizational maturity. Ultimately, this paper underscores AI's pivotal role in advancing Industry 4.0 by facilitating data-driven maintenance that is both intelligent and proactive.

Keywords: Predictive Maintenance (PdM), Artificial Intelligence (AI), Industry 4.0, Machine Learning (ML), Internet of Things (IoT), Deep Learning, Remaining Useful Life (RUL), Condition Monitoring.

INTRODUCTION

Machine learning (ML) in predictive maintenance provides the opportunity to use information and models to predict the future and prepare appropriate actions. Data-based predictive maintenance is a new, emerging research topic, and the interest attracted is explosive. A review of effective data-driven predictive maintenance has been conducted to identify and summarize effective methodologies from the perspectives of the data-driven predictive maintenance problem, data, model, and evaluation. The direction for future studies and extensive, benchmark datasets for reverse research are also expected to be provided. The importance of maintaining the production system responsibly is growing with the demand for faster and more flexible manufacturing. One key to practicing appropriate maintenance actions on the right components at the right time is to derive the knowledge of the system from failure history. Emerging prediction models such as Deep Neural Networks (DNNs) could learn the temporal characteristics of working condition data and predict the Remaining Useful Life (RUL) to respond to the system's health. Predictive maintenance (PM) is an improved process of corrective and preventive maintenance, facilitating IT management to lead toward a greener economy by anticipating machine failures before they occur. This paper focuses on the key ingredients for a predictive maintenance methodology in the manufacturing domain. This work defines the scope and concepts of predictive maintenance. Maintenance, in general, is the ability to take actions to keep the production system working flawlessly. There are three types of maintenance based on actions: unscheduled maintenance to take actions after components fail, scheduled maintenance to take actions before components fail, and predictive maintenance to take actions on components' health diagnostic information in advance of a failure [1, 2].

The Role of Artificial Intelligence

Artificial Intelligence (AI) is transforming a wide range of fields around the world and is considered a key factor in the advancement of the Fourth Industrial Revolution. AI is being applied to a wide range of issues, with predictive maintenance (PdM) gaining popularity in industrial contexts as an area of interest. Industries using PdM maximize profits by reducing their overall operational costs, shutting down machines on time, and preventing unforeseen accidents. It is worth mentioning that industrial sectors like oil, chemical, steel, and the paper industry bring demand for PdM applications; therefore, they are mostly relevant for those industries. PdM is the maintenance of the components that need maintenance. It is accomplished by continuously testing the monitored operating parameters and predicting the future course of the parameters and the statistical distribution under which they will evolve. The maintenance activity triggered by this method eliminates, with high probability, the degradation state of the monitored component before it fails Development of this preventive decision-making method is the goal of many research works dedicated to data processing useful for maintenance, signal conditioning techniques, statistical analysis methods on historical or real-time data, and models simulating the components of the technical systems, leading to the choice of the decision model. Because of the Zero-Fail Principle (ZFP), there is an increasing need for the implementation of the preventive decision model. Maintenance operations should be discussed in conjunction with the failure phenomenon they are aimed at dealing with. This phenomenon has many definitions, for example, "an unplanned event that decreases the capability of a system or part of a system towards the performance of its design functions" [3, 4].

Data Collection Techniques

Data is the backbone of every AI model used for predictive maintenance. Almost all industry systems today are equipped with thousands of sensors. These sensors collect huge amounts of data each second. However, for most industries to utilize data for AI, it first needs to be collected and organized in a database that is accessible to Data Scientists. This usually involves software-based acquisition programs that can be run on the computer receiving real-time data from the machines. Bulk data push via flat files is always a good alternative. However, it requires intensive work in defining controlling versions and rules to organize the push data types as organizations grow and more machines come online. And for many industries, other systems controlling historical sensors are just pushing data to flat files without much organization, and then at that point, it is already too late to affect how data is structured. Data labeling is almost always needed for solving prediction problems. In some cases, such as quality prediction, a process model already specifies the quality types. However, for most cases, the machines being monitored by AI are merely different in the process of being built for the same intended purpose. When the models are first launched, unfortunately, almost all of them will initially suffer from frizzing and other technical issues. These scenarios are sometimes at the very fundamental level and usually don't leave any signs in the historical process data. And labeling the data that relates to these scenarios often needs human efforts. Even once the labeling effort dried up, as usage scenarios evolve continuously with changes in patterns and data specifications of failures, data retraining is always needed to preserve prediction performance, which often requires vast amounts of newly labeled data. This manual work is laborious and susceptible to human-made mistakes. Therefore, it usually becomes a bottleneck for predictive maintenance in industries [5, 6].

Data Processing and Analysis

For predictive maintenance application in a factory with many machines, a data model is needed to capture infrastructure information of machines, automate data acquisition of the data needed for analysis and decision-making. A data model captures data from the resources and their dependencies. It makes maintenance data available for the decision-makers. The data model for predictive maintenance in flexible manufacturing captures data from the sources and their dependencies. It depicts ten classes: resource, machine repository, maintenance repository, maintenance schedule, machine, component, process, machine base, data requirement, and dependencies. There are also 12 relations modelling their dependencies. Predictive maintenance is a decision support system that analyses data from the machines to detect conditions indicating that maintenance is required. Data from the machines is taken as input. It predicts the remaining useful life (RUL) of machine components and estimates the probability that maintenance is required in a certain time window. Returned data can be machine-specific, component-specific, or task-specific. For example, the RUL of a machine can be obtained, from which RULs of different components can be derived, e.g., starting bearing and coil bearing. The RUL of a Machining task can be obtained based on the process variable of the task. It is possible for maintenance task descriptions to be machine-specific, component-specific, or task-specific. Machines will require maintenance when the condition of a machine or component exceeds defined limits. This can be decided on the collected machine data, which defines dependencies between machine and component parameters, data requirements for operations, and prediction data. The condition assessment and the prediction of how PID values will change in the future are performed based on the data stored in the machine repository. A flexible manufacturing factory is composed of different machines, and multiple machines of each type are used in the machine repository, such as one type of robot, a CNC machine, or conveyor robots. This repository captures general information on the resources and requirements for existing machines and components [7, 8].

Machine Learning Algorithms

Machine learning in manufacturing is a growing area of interest, with many potential benefits, including reduced downtime, reduced costs, and improved reliability. However, a number of challenges, such as data acquisition and fusion, machine learning model training, and change management, need to be properly addressed. An implementation for the predictive maintenance of textile machines based on a fuzzy logic approach shows how a hybrid machine learning model could help fulfill some of the requirements for a successful implementation. A steel production implementation, on the other hand, shows how a maintenance process could be analyzed and improved by creating an information model through data reconciliation and integrations with other data sources. In today's technology world, every machine and tool, especially in the manufacturing sector, has its own favorable life, and after many uses and operations, it deteriorates. Not only this, but it also has to bear some accidental and operational defects, whether they are sudden breakdowns or failures. The underlying cause of these may be operational, technical, or it can be something else. The need for predictive maintenance and advanced predictive diagnostics has crept into ALL machinery, whether it is aviation, ships, automobiles, or rotating and moving machines. The need is one: to know the damages, failures, and operational defects beforehand to avoid any drastic or hazardous conditions. Predictive maintenance is nothing but advice to maintain machinery and tools at certain intervals of time beforehand in order to save working time and improve the lifetime of the machine, thus improving the overall operational efficiency. The architecture of the study is as follows. First, some worth reading and informative literature surveys and reviews are being presented. Then comes the technical part of the study, where the implementation of the proposed methodology is depicted in detail. Starting from the machine or data acquisition, data preprocessing and formatting, reverse engineering of data, and descriptive and predictive analytics are thoroughly covered. Finally, the conclusion and future scopes are discussed as a last note to sum up the whole work [9, 10].

Predictive Models Development

Achieving predictive maintenance (PdM) of an industrial system requires monitoring of the performance of its components through predicting how and when one of them is going to fail and stop operation. In order for this prediction to take place, the part must be continuously monitored by various sensors (mainly IoT sensors) and simultaneously gather and save a lot of data. These data should then be forwarded to a state-of-the-art maintenance prediction model, and the model predicts on an Ad hoc basis the part replacement. Many maintenance prediction models have been developed until now, but the most popular models combine predictive analysis with machine learning (ML) methods. The implementation of ML techniques for PdM requires, firstly, the collection of relevant data about the operating time history of each component of the system and any idle state and performance values. These data are then generated into useful features, and finally, a series of advanced classifiers are applied to achieve the prediction. These ML-based models give the industry a predictive maintenance (PdM) approach, which saves on average 15% annual costs compared to planned maintenance, and because no immediate action is required for the prediction alarm, more downtime due to premature replacements is avoided. Modern techniques for feature extraction include vibration-acoustic analysis, infrared monitoring, and model-based condition analysis. Various sensors are installed in the device where PdM applies without affecting the operation of the main component. A Wireless Network is developed, and various wireless protocols can be used to implement this network. For high data rate and low-power type sensors, the wireless mesh networking protocol is more effective; otherwise, a point-to-point connection is feasible. The sensors are placed next to bearings, gears, and pumps, etc., which are the parts that mostly affect the overall performance of the device. The current trend in data processing and analysis is the use of ML methods. Machine learning has evolved into a powerful tool that implements high-quality intelligent algorithms for prediction. A feature of ML is the ability to process big data and, therefore, effectively find hidden correlations. These data can be complex and produced in constantly changing environments. This contribution highlights the areas where PdM is applied most often, the most common measurement sensors, as well as the most prevalent ML models applied to PdM. The challenges of predictive maintenance are presented, specifically the problem of obtaining quality data for implementation. When ML is applied to PdM, it follows a process consisting of specific stages. The aim is to achieve successful prediction for maintenance [11, 12].

Implementation Strategies

The logic of the methodology follows the value chain through twelve groups of techniques applicable at different phases of the value chain activities. Most techniques were additionally allocated to phases into three groups according to their applicability (the "basic" ones are most widely used or are very straightforward for application, the "advanced" ones are slightly less frequently applied or more complex in application, and the "complementary" ones should be applied when there are high requirements concerning these phases). For this reason, 24 smaller groups of techniques were created and presented in the workflow diagrams. These diagrams also indicate potential open issues in a different color. The connection of the depicted approaches with the state-of-the-art techniques is also indicated. It also presents a visual illustration of the implications of an analysis of impacts on the choice of an effective approach to PD. All techniques differ in terms of effort required for their implementation, relative to the complexity or timeframe of implementation. There are also diverse impacts of such an approach on organizations. Some solutions have relatively low impacts and are least demanding from the organization's perspective, e.g., simple preventive or condition-based maintenance. Some others require relatively huge efforts and, thus, have the greatest impacts on organizations in line with the organizational actors' hierarchy, e.g., the implementation of Superior Machine Learning and Total Productive Maintenance (TPM)-like initiatives. Requirements are defined for each weight/effort to increase the probability of suitable actions. The results of initial pilot applications of personalized procedures for less mature organizations are also presented. Performed analyses indicate that maintenance maturity and the competitor analysis stage are keys in selecting the most appropriate techniques and change strategy, while computerized tools or models should not be prioritized too early and should come primarily in the cases of mature organizations as part of greater implementations [13, 14].

Case Studies

The importance of computational devices is rapidly expanding due to their practical applications in every industrial facility. Nevertheless, the operational safety of computing devices and their networking infrastructure must not be disregarded. Practicing predictive maintenance in networks is vital, as computing devices are exposed to process errors due to abrupt changes in network inputs. Past faults can likewise provide further insight into the current task environment, improving decision-making accuracy and reliability. In a local area network containing industrial devices, monitoring the state of devices is crucial to fully understand the current situation of the network and mitigate unsafe conditions. For this case study, an access point approach using deep learning techniques to examine past latencies in industrial devices and obtain predictive knowledge for several time steps into the future is presented. Additionally, the approach's capability to distinguish between sound operational devices and devices that are going to errors is evaluated. The datasets utilized in this case study consist of latency values, which record the connection establishments of each device at each time increment. In terms of error diagnosis, the provided latent vector can facilitate that examination and aid in understanding how and why errors occurred in devices. This work is primarily motivated by the need to maintain the functionality and productivity of the production facility, which would be a critical challenge since the optimization of facilities will have to be conducted without designating a stand-alone period. Predictive maintenance has been an important topic for devices in industrial facilities. Since every device is implemented with sensors, IoT technology has been raised to obtain a comparatively large amount of process information. Additionally, deep learning techniques are adopted to detect operational anomalies in order to notify operators of any irregularity and preserve optimal operation. These approaches are concerned with monitoring the state of devices. Predictive maintenance for networking infrastructure is proposed by providing a detailed description of devices and their maintenance rules. A case study using past latencies of a local area network containing industrial devices has been presented [15, 16].

Benefits of AI in Predictive Maintenance

Predictive maintenance is the most advanced approach compared to traditional methods. While corrective maintenance occurs post-defect and scheduled maintenance incurs unnecessary expenses, predictive maintenance leverages the Internet of Things and affordable sensors. Integrating machine learning into predictive maintenance enhances its popularity across industries. It involves monitoring machine conditions using deep learning methods, leading to significant performance improvements. Much research centers on machine learning techniques, though other models also serve production and logistics. This article reviews machine learning in predictive maintenance, emphasizing data-driven techniques and applications, alongside an overview of datasets for training. It discusses predictive maintenance models, sensors for data collection, public datasets, and IoT communication protocols. The key to modern applications is the processing of large datasets via cloud platforms, crucial for high-frequency data tasks. The article outlines major machine learning model type's unsupervised, supervised, and deep learning\ explaining their principles and popular implementation tools. Benefits of these models in industrial applications, including Industry 4.0, IoT, Edge computing, and Cloud computing solutions, are also addressed [17, 18].

Challenges and Limitations

In the 21st century, industries have significantly enhanced their production processes using emerging technologies. IoT, Artificial Intelligence (AI) and Machine Learning, edge and cloud computing, and data analytics are only a few of these technologies. These technologies can promote condition monitoring, failure detection, diagnosis, and reliability assessment of production equipment. PdM is a maintenance philosophy that has been gaining much attention from industries. A big part of industrial production depends on the operation of mechanical devices, machines, and equipment. Many of these devices perform in destructive environments and for extended operating times. Hence, they are prone to wear out and might suffer from degradation, which in turn might lead to a decrease in their functionality and efficiency or even cause catastrophic failures. Three categories of maintenance can promote the operation of this equipment, considering its application time: unscheduled maintenance, scheduled maintenance, and predictive maintenance. Unscheduled maintenance (also referred to as corrective or run-to-failure maintenance) occurs after a component's or equipment element's failure. A large number of electrical and mechanical components can suffer from state degradation in a deterministic manner. However, most industrial equipment consists of subsystems that include interacting components of different types. Hence, most failures are the consequence of the interdependencies of interacting components and the resulting cascading effects through the products and processes. This interdependency is essential in evaluating and designing maintenance policies; it makes unscheduled maintenance costly. Moreover, the time needed to repair complex electronic components or change some assembly components is significant. This can result in a complete production stop with severe financial losses. Thus, industries cannot afford to run-to-failure maintenance for complex and expensive manufacturing equipment [19, 20].

Future Trends in Predictive Maintenance

Strategies are increasingly adopted by developed economies transitioning to digitization, with Artificial Intelligence playing a key role. The evolution of Industrial Analytics builds on earlier waves of Computational Intelligence and Data Analytics, where Big Data transformed industrial process data automatically. Modern Big Data Automated Analytics ingests and analyzes raw data across various formats, yielding insights for decision-making. Over the last decade, Cloud Computing emerged, enabling major industries to deliver commercial services that were once confined to research centers. A notable sector is Predictive Maintenance (PdM), which predicts asset maintenance needs using historical and real-time data across multiple dimensions like weather and asset health. PdM can be implemented as a single platform or as a comprehensive solution that includes data ingestion, storage, machine learning, visualization, ETL, and reporting. In 2016, research investigated Industry 4.0 and IoT related to PdM through a global survey examining this lucrative sector. Analysis over the past century has revealed trends in industrial smart analytics and PdM. Current research offers insights into the commercial landscape of IoT applications, focusing on usage metrics, sectors, providers, and regions, providing a glimpse into future developments and preparations for rapid advancements [21, 22].

Ethical Considerations

In recent years, concerns about the ethics of Artificial Intelligence (AI) systems have grown, leading to guidelines for ethical AI development. However, task-specific algorithms like predictive maintenance fail to incorporate ethical considerations like safety and bias, focusing solely on user recommendations based on training data. Addressing broader societal issues, such as the ethics of automating maintenance jobs with affordable sensing technology, raises important questions about the acceptable removal of skilled labor. If ethical concerns hinder system acceptance, the technology might never be implemented. AI can reinforce human decisions, but fairness is crucial; bias emerges when training datasets are flawed, leading to misrepresentations in recommendations. For instance, if maintenance data for machine type X is confined to a community, another machine type must be selected for the AI. Overfitting also introduces bias risk. As AI assumes more tasks, its decision-making process risks becoming unclear, jeopardizing trust and safety. AI-assisted recommendations are prevalent, but erroneous suggestions can result in danger, underscoring the need for explainability. Simpler models like decision trees can enhance transparency. In image recognition, AI suggests labels based on its model, while efforts continue to clarify the features utilized for predictions. Running predictive maintenance models outside the training conditions poses safety risks; accordingly, the optimal output and inspections for reliability may act as safety nets. To mimic human decision-making in predicting failure rates, exploratory data analysis precedes recommendations [23, 24, 25].

CONCLUSION

The integration of Artificial Intelligence into predictive maintenance systems represents a paradigm shift in industrial operations. By leveraging AI technologies, particularly machine learning and deep learning, industries can move from reactive and scheduled maintenance models to proactive strategies that significantly reduce downtime, extend equipment lifespan, and lower maintenance costs. AI enables more accurate forecasting of component failures by analyzing real-time and historical data, thus enhancing decision-making processes. While the advantages are clear, implementation challenges persist, especially in data labeling, model training, and infrastructure readiness. Moreover, organizational factors such as maturity level and readiness to adopt AI-driven tools also influence success. As industries continue to evolve under the influence of Industry 4.0, the fusion of AI with predictive maintenance not only optimizes performance but also sets a foundation for fully autonomous industrial systems. Future research should focus on standardizing data practices, improving model interpretability, and ensuring cybersecurity in AI-powered maintenance environments.

REFERENCES

1. Abidi MH, Mohammed MK, Alkhalefah H. Predictive maintenance planning for industry 4.0 using machine learning for sustainable manufacturing. Sustainability. 2022 Mar 14;14(6):3387.
2. Bouabdallaoui Y, Lafhaj Z, Yim P, Ducoulombier L, Bennadji B. Predictive maintenance in building facilities: A machine learning-based approach. Sensors. 2021 Feb 3;21(4):1044. mdpi.com
3. Mikołajewska E, Mikołajewski D, Mikołajczyk T, Paczkowski T. Generative AI in AI-Based Digital Twins for Fault Diagnosis for Predictive Maintenance in Industry 4.0/5.0. Applied Sciences. 2025 Mar 14;15(6):3166.
4. Achouch M, Dimitrova M, Ziane K, Sattarpanah Karganroudi S, Dhouib R, Ibrahim H, Adda M. On predictive maintenance in industry 4.0: Overview, models, and challenges. Applied Sciences. 2022 Aug 12;12(16):8081. mdpi.com
5. Rojas L, Peña Á, Garcia J. AI-driven predictive maintenance in mining: a systematic literature review on fault detection, digital twins, and intelligent asset management. Applied Sciences. 2025 Mar 19;15(6):3337.
6. Zong Z, Guan Y. AI-driven intelligent data analytics and predictive analysis in Industry 4.0: Transforming knowledge, innovation, and efficiency. Journal of the Knowledge Economy. 2024 May 8:1-40.
7. Ong KS, Wang W, Niyato D, Friedrichs T. Deep-reinforcement-learning-based predictive maintenance model for effective resource management in industrial IoT. IEEE Internet of Things Journal. 2021 Sep 3;9(7):5173-88. [HTML]
8. Ayvaz S, Alpay K. Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time. Expert Systems with Applications. 2021 Jul 1;173:114598.
9. Pech M, Vrchota J, Bednář J. Predictive maintenance and intelligent sensors in smart factory. Sensors. 2021 Feb 20;21(4):1470.
10. Yazdi M. Maintenance strategies and optimization techniques. Advances in Computational Mathematics for Industrial System Reliability and Maintainability 2024 Feb 25 (pp. 43-58). Cham: Springer Nature Switzerland. [HTML]
11. Drakaki M, Karnavas YL, Tziafettas IA, Linardos V, Tzionas P. Machine learning and deep learning based methods toward industry 4.0 predictive maintenance in induction motors: State of the art survey. Journal of Industrial Engineering and Management (JIEM). 2022;15(1):31-57. econstor.eu

12. Arena F, Collotta M, Luca L, Ruggieri M, Termine FG. Predictive maintenance in the automotive sector: A literature review. Mathematical and Computational Applications. 2021 Dec 31;27(1):2. mdpi.com
13. Karunarathna I, De Alvis K, Gunasena P, Jayawardana A. Designing and conducting clinical research: Methodological approaches. Journal of Clinical Research. 2024:1-3. researchgate.net
14. Imam MS, Abdelrahman MM. How environmentally friendly is the analytical process? A paradigm overview of ten greenness assessment metric approaches for analytical methods. Trends in Environmental Analytical Chemistry. 2023 Jun 1;38:e00202. [HTML]
15. Zhong D, Xia Z, Zhu Y, Duan J. Overview of predictive maintenance based on digital twin technology. Heliyon. 2023 Apr 1;9(4).
16. Teoh YK, Gill SS, Parlikad AK. IoT and fog-computing-based predictive maintenance model for effective asset management in Industry 4.0 using machine learning. IEEE Internet of Things Journal. 2021 Jan 11;10(3):2087-94.
17. Samatas GG, Moumgiakmas SS, Papakostas GA. Predictive maintenance-bridging artificial intelligence and IoT. In2021 IEEE World AI IoT Congress (AIIoT) 2021 May 10 (pp. 0413-0419). IEEE.
18. Eze VH, Uche CK, Okafor O, Edozie E, Ugwu Chinyere N, Chukwudi OF. Renewable Energy Powered Water Supply System in Uganda: A Critical Review. Renewable Energy. 2023;3(3).
19. Molęda M, Małysiak-Mrozek B, Ding W, Sunderam V, Mrozek D. From corrective to predictive maintenance—A review of maintenance approaches for the power industry. Sensors. 2023 Jun 27;23(13):5970.
20. Bag S, Rahman MS, Srivastava G, Chan HL, Bryde DJ. The role of big data and predictive analytics in developing a resilient supply chain network in the South African mining industry against extreme weather events. International Journal of Production Economics. 2022 Sep 1;251:108541. ljmu.ac.uk
21. Annapareddy VN, Seenu A. Generative AI in Predictive Maintenance and Performance Enhancement of Solar Battery Storage Systems. Predictive Maintenance and Performance Enhancement of Solar Battery Storage Systems (December 30, 2023). 2023 Dec 30. ssrn.com
22. Bhanji S, Shotz H, Tadanki S, Miloudi Y, Warren P. Advanced enterprise asset management systems: Improve predictive maintenance and asset performance by leveraging Industry 4.0 and the Internet of Things (IoT). InASME/IEEE Joint Rail Conference 2021 Apr 20 (Vol. 84775, p. V001T12A002). American Society of Mechanical Engineers. berger-levrault.com
23. Keleko AT, Kamsu-Foguem B, Ngouna RH, Tongne A. Artificial intelligence and real-time predictive maintenance in industry 4.0: a bibliometric analysis. AI and Ethics. 2022 Nov;2(4):553-77.
24. Mota B, Faria P, Ramos C. Automated machine learning and explainable artificial intelligence in predictive maintenance: An mljar framework review. InInternational Symposium on Distributed Computing and Artificial Intelligence 2024 Jun 25 (pp. 150-159). Cham: Springer Nature Switzerland.
25. Hazra S. Review on Social and Ethical Concerns of Generative AI and IoT. InGenerative AI: Current Trends and Applications 2024 Dec 10 (pp. 257-285). Singapore: Springer Nature Singapore.

CITE AS: Awafung Emmanuel (2025). Artificial Intelligence in Predictive Maintenance for Industry. NEWPORT INTERNATIONAL JOURNAL OF SCIENTIFIC AND EXPERIMENTAL SCIENCES 6(3):7-13 https://doi.org/10.59298/NIJSES/2025/63.713