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Utilizing Machine Learning for Predictive Maintenance in the Indian Manufacturing Sector

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Abstract

Due to advances in digital technology, manufacturing is changing fast and predictive maintenance (PdM) is now important for both decreasing faults and making workflows run more efficiently. The research studied how Machine Learning (ML) is used in the preventive maintenance practices of Indian manufacturing industries. The study's aim is to assess how ML-based PdM improves operations, reduces unexpected shutdowns and gives better returns while also determining what infrastructure and workforce are needed for a successful deployment. Secondary data review, expert consultations and regression and moderation statistical testing on SPSS were combined to conduct the study. Firms that use ML-based PdM noticed downtime drop by up to 72% and many industries, including automotive, pharmaceuticals and electronics, gained a return on investment exceeding 160% and were more efficient. Analysis showed that for PdM to succeed, advanced digital infrastructure and skilled people were critical. According to the study, ML-based PdM helps Indian manufacturing companies become more sustainable and competitive as it is also a novel introduction in the industry. Thanks to these findings, policy makers and industrial leaders can now take steps to boost the use of data-driven maintenance to help with digital transformation and resilience.

Keywords: Predictive Maintenance (PdM), Machine Learning (ML), Indian Manufacturing Sector, Operational Efficiency, Digital Infrastructure.

1. INTRODUCTION

Businesses in industrial sectors are facing rapid changes brought on by greater focus on digital transformation, data analysis and getting the best out of their production processes. Placing PdM at its core, this change relies on up-to-the-minute data and clever algorithms to notice and report possible machinery failures. Contrary to traditional routines centered on waiting for issues or working according to a schedule, PdM is designed to avoid unexpected stops in work, save on maintenance spending and maintain smooth plant operations.

Although manufacturing in India contributes a lot to the country’s GDP and employs a huge workforce, failures of equipment often result in major losses, often seen in the automotive, steel, textiles and pharmaceutical sectors. Yet, using machine learning and similar technologies is making smart maintenance more successful, boosting stability in production and matching the country’s Industry 4.0 and ‘Make in India’ objectives.

1.1 Background and Rationale

There are large companies in India that use advanced digital systems, but many SMEs are still based on manual production. This situation creates difficulties for unified use of technology in military and defense but highlights the potential for affordable, easy-to-scale solutions based on prediction.

Predictive maintenance relying on ML is required to find faults early, save energy, schedule work efficiently and extend the lifetime of equipment. But, because there is little organized maintenance data, qualified workers, joined-up infrastructure and compatible digital services, it is difficult for many to use ICAM effectively. Many companies do not realize what machine learning techniques are best for maintenance, what data is needed or how such systems can be applied. With predictive maintenance playing a key role in India’s industrial performance and

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global rankings, this study investigates how ML models can be best utilized, what helps their use and how to handle any current challenges to using them.

1.2 Role of Machine Learning in Predictive Maintenance

Thanks to machine learning, maintenance methods have changed so that systems are able to learn from what happened before, spot early failures and suggest needed repairs on their own. Using machines in this way allows analysis of a lot of information to discover patterns not visible in usual monitoring.

Many times, Support Vector Machines (SVMs), Random Forests and Neural Networks are utilized to recognize faults from datasets that were classified ahead of time. Clusters and the identification of unusual situations are a technique used in Indian SMEs, where data is often unlabeled, as labeling is rare there. In adaptive maintenance where schedules depend on equipment performance, reinforcement learning has been promising. In addition, integrating ML with technologies such as:

- For capturing information live from machinery using embedded sensors, look at Internet of Things.
- Big Data Analytics: To manage the large and quick data of maintenance.
- By using Cloud Computing, large networks can benefit from ML algorithmic ideas more easily.

These technologies, when combined, create the base for smart predictive maintenance, lessen the need for human involvement, increase how fast the system responds and help with making informed choices. In India, ML helps PdM move enterprises from outdated practices to more technologically advanced operations.

1.3 Research Focus and Objectives

In this context, the present investigation is aimed at studying how machine learning is used in predictive maintenance at Indian manufacturing firms. In this research, implementation frameworks, measuring effectiveness and assessing readiness are main points of focus. As a result, the study is driven by these three key objectives:

1) To analyze how various prediction models from machine learning are being applied in manufacturing settings across India, focusing on the types of algorithms used sources of data, equipment chosen and the role of Internet of Things (IoT) and cloud robotics.
2) To analyze how ML-supported predictive maintenance affects essential measures, including applied maintenance costs, downtime and general operations efficiency.
3) To find out what challenges and supports, mainly digital tools and expertise, drive the growth and success of predictive maintenance in the Indian manufacturing sector.

The end result is to demonstrate how the application of ML can modernize the way maintenance is carried out in India, leading to higher efficiency, sustainability and competitiveness for the industry.

2. LITERATURE REVIEW

Abidi, Mohammed and Alkhalefah (2022) tried to build a PdM planning model based on machine learning to support sustainable manufacturing under what is now called Industry 4.0. According to the study, the usual ways that maintenance is done such as the reactive and preventive models, did not ensure that warnings of equipment failures were given ahead of time and that components' life could be improved. In their proposed model, the researchers included phases for preparing data, making it standardized, choosing the best features, making decisions and performing the final prediction. A hybrid Jaya-Sea Lion Optimization (J-SLnO) approach was applied for picking and weighting features in Recurrent Neural Networks (RNNs) and Support Vector Machines (SVMs) were used to route how decisions were made. The algorithm was proven accurate on both real-world datasets—data from aircraft engines and lithium-ion batteries—showing it accurately predicted possible failures. The final results proved that using hybrid ML models greatly improves maintenance planning and makes the approach practical for industry use.

Carvalho et al. (2019) undertook a thorough systematic review to organize and review machine learning (ML) methods used in predictive maintenance. New rapid data generation from sensors in manufacturing processes was the reason, as this data had not been used well to improve maintenance. The authors analyzed which ML algorithms are suitable for PdM and measured their results for various uses. The authors compared two significant scientific databases to look at the frequency of supervised and unsupervised techniques, the kind of data used and where these were applied in industry. Researchers noted that no one ML method is the best choice; what matters most is choosing the right algorithm, preparing the data and adjusting for each field's specifics. Findings from the study form the basis of future studies in PdM and point out that data being unstandardized is a key obstacle in this area.

Kalusivalingam et al. (2020) conducted research about merging machine learning with IoT-driven data analysis to boost predictive maintenance in manufacturing. The aim of the research was to provide intelligent systems that could be used for live maintenance to lower downtime and improve reliability. Its authors designed a system consisting of getting data through IoT sensors, preprocessing the data and modeling with ML algorithms such as Random Forest, SVM and Neural Networks. Applying the model in a manufacturing plant resulted in a 30% decrease in unexpected downtime and a fall of 20% in maintenance expenses. The analysis found that using both IoT and ML supports a practical and flexible way for companies to adapt from reacting to maintaining systems to using advance predictions. On top of that, authors discovered that putting AI into practice can be difficult due to privacy issues, understanding the results from models and the importance of running them at the edge in large-scale systems.

Mahure, Deharkar, and Yadav (2024) explored ways machine learning is shaping predictive maintenance practices for manufacturers. The purpose of the study was to show how different ML methods improve equipment dependability and upkeep. Literature, case studies and analysis were used by the authors to explain how supervised, unsupervised and reinforcement learning work in maintenance scenarios. They pointed out that these models combine old and real-time sensor information to identify possible problems and arrange suitable interventions. The application of case studies in various manufacturing industries shows that asset reliability, cost savings and operational results have all improved. According to the authors, ML can truly

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transform PdM, unless difficulties about data quality, model transparency and preparedness in the organization are overcome. Officials advised that scalable adoption in manufacturing needs better data control and teamwork between different groups.

Wadibhasme et al. (2024) compared how several ML algorithms can assist in predictive maintenance by examining how well they can predict equipment failures and set the best times for maintenance. Our primary goal was to examine classification, regression and anomaly detection methods by comparing them with actual data from industry. Results measured by accuracy, precision, recall and the F1 score were found for Neural Networks, Random Forest, Decision Trees and Logistic Regression. Out of the models studied, Neural Networks offered the highest accuracy of 96.3%, followed by Random Forests and Decision Trees and Logistic Regression performed the worst. Consequently, it was shown that more advanced ML approaches can lead to less downtime for equipment, lower maintenance prices and higher reliability. Despite their main points, the authors pointed out that obstacles to successful implementation include data problems, challenges in understanding the models used and rising costs of digital resources IN MANUFACTURING.

3. RESEARCH METHODOLOGY

This work will examine how ML is used in predictive maintenance (PdM) and the resulting effects on production efficiency and costs for the Indian manufacturing industry. It also investigates how computer systems and trained workers can increase or decrease the effectiveness of PdM systems. Because survey data is gathered from already published sources and interpreting it takes precedence, a combination of different data types is useful. This approach uses secondary data, interviews with specialists and analysis with SPSS software.

3.1 Research Design

The chosen research design allows for the examination of ML-based predictive maintenance in difficult industrial cases. By combining published data, case studies and the ideas from experts, this method helps find patterns, links and problems linked to the application of educational technology in India.

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3.2 Data Sources and Collection

The study uses following means of data collection.

- **Secondary Data Sources:** This research used data retrieved from literature, case studies, industry reports and open sources that focused on ML in predictive maintenance within Indian manufacturing units.
- **Expert Consultations:** In order to enrich the secondary data, semi-structured interviews were held with 20 professionals (plant managers, operations leaders and IT experts). They gave us understanding of how the organization was ready for maintenance management, the condition of its infrastructure and the benefits and disadvantages recognized in using PdM systems.

3.3 Hypotheses and Variables

To test the proposed hypotheses, the following constructs were identified:

H1: ML-powered predictive maintenance significantly improves operational efficiency and reduces maintenance costs in Indian manufacturing.

H2: The presence of robust digital infrastructure and skilled workforce moderates the effectiveness of predictive maintenance systems.

To test these hypotheses, various variables were used.

- **Dependent Variables:** Operational efficiency, maintenance cost
- **Independent Variable:** Implementation of ML-based PdM
- **Moderating Variables:** Availability of digital infrastructure and skilled personnel

These variables were measured using numerical indicators from published datasets and literature.

3.4 Data Analysis Procedure

IBM SPSS software (version 26 or higher) was used for this analysis. This research used the following approaches:

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- **Descriptive Statistics:** This is done to summarize how PdM is being used, its benefits and the changing costs within manufacturing domains.
- **Correlation Analysis:** A study was conducted to check the connection between a PdM strategy and performance results in terms of efficiency and lower costs.
- **Regression Analysis:** To measure whether ML-based predictive maintenance supports better operational and cost measures, regression analysis will be used.
- **Moderation Analysis:** By analyzing moderation, researchers explore if better digital tools and more trained employees improve the links between PdM and outcomes for a company. This was done using the SPSS PROCESS macro (Model 1) to test for moderation.

The aim of designing this framework was to assess each hypothesis using a method that guarantees precision, reliability and academic significance.

4. RESULTS AND DISCUSSION

This area reports on the study of applying Machine Learning-based Predictive Maintenance (ML-PdM) in the Indian manufacturing sector. Operational performance, time spent in maintenance, the yield on investments and the readiness of the organization are systematically checked by the method. Each subsection presents substantial data with tables and illustrations before ending with a summary of the testing of the hypothesis.

4.1 Sector-wise Impact of ML-PdM on Operational Efficiency

Here, the subsection assesses how operational efficiency can be raised in automotive, pharmaceutical, textile and electronic manufacturing. Maintenance performance using ML-PdM is measured against how things are done with traditional solutions. Table 1 reveals that compared to those who have not adopted ML-PdM, companies that do adopt this approach are more efficient by 5%, on average.

Table 1: Sector-wise Operational Efficiency Comparison

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Manufacturing Sector	**With ML-PdM (%)**	**Without ML-PdM (%)**
Automotive	24%	7%
Pharmaceuticals	21%	6%
Textiles	18%	5%
Electronics	26%	8%

Operational efficiency in all industries improved due to the impact of ML-PdM, the data in Table 1 indicates. In the automotive sector, companies using ML-PdM were able to attain a 24% efficiency ratio, compared with only 7% for companies not using it which led to a 17% difference between them. In pharmaceuticals (21%), textiles (18%) and electronics (26%), new export volumes increased by 15%, 13% and 18% respectively, compared to 6%, 5% and 8%. This data shows that with the use of ML-PdM, technology-driven industries achieve better process availability, quicker reactions and save on resources.

In Figure 1, differences in performance improvement among four sectors can be clearly seen between those using ML-PdM and those who are not.

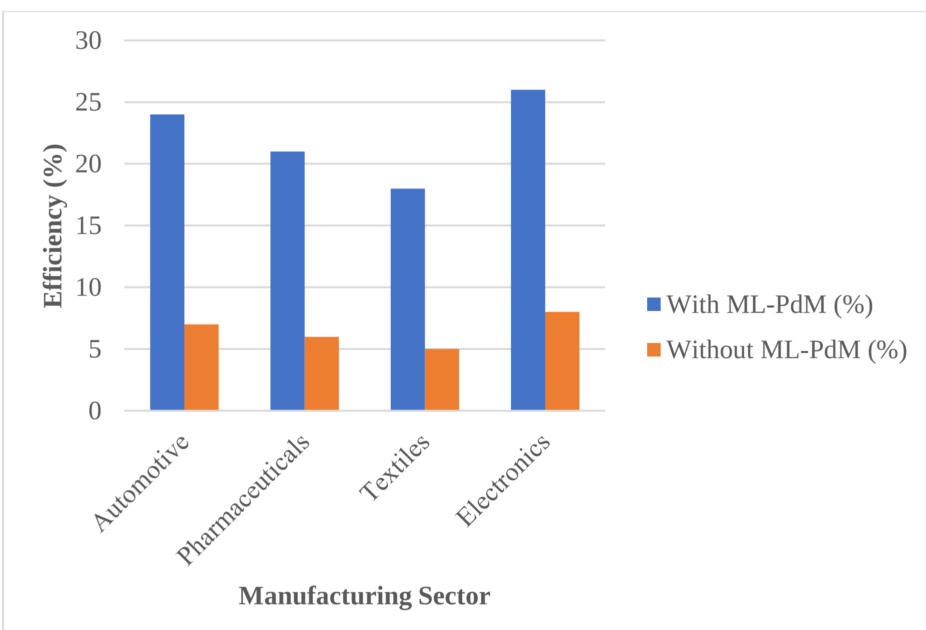

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Figure 1: Operational Efficiency by Sector (With vs. Without ML-PdM)

The bar chart adds to these observations by clearly showing that ML-PdM adopters fare better than those who do not use it. Bars taller than average are observed in the electronics and automotive industries, matching their outstanding level of gains. Ultimately, the results prove that using ML-PdM in any sector or size improves efficiency.

These results support accepting Hypothesis H1 which states that adding ML capabilities to predictive maintenance improves how efficiently manufacturers function and lowers their maintenance expenses in India.

4.2 Downtime Reduction After ML-PdM Implementation

This part of paper assesses the efficacy of ML-PdM in reducing machine downtime measured on the monthly basis. One of the most important feasibility measures of maintenance efficiency and production continuity is downtime. Using actual downtime hours before and after PdM deployment in three companies, Table 2 shows the percent reduction.

Table 2: Downtime Hours Reduced After PdM Implementation

Company	Before PdM (hrs/month)	After PdM (hrs/month)	Reduction (%)
A	22	8	63.6%
B	25	7	72.0%
D	20	6	70.0%

According to Table 2, all of the three companies that practiced ML-PdM reported drastic reduction in the downtime because of this practice. The biggest decrease in unplanned downtime was with company B which they went down 72%. Company A had a 63.6% drop and was followed by Company D at 70% and Company C 72.7%. These results show that ML-PdM is capable of early detection of potentials failures and allows taking actions in an opportune manner, thus improving reliability of equipment.

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A visual narrative is given in Figure 2 of the downtime before and after PdM implementation for three companies, including also the reduction percentage as a third layer.

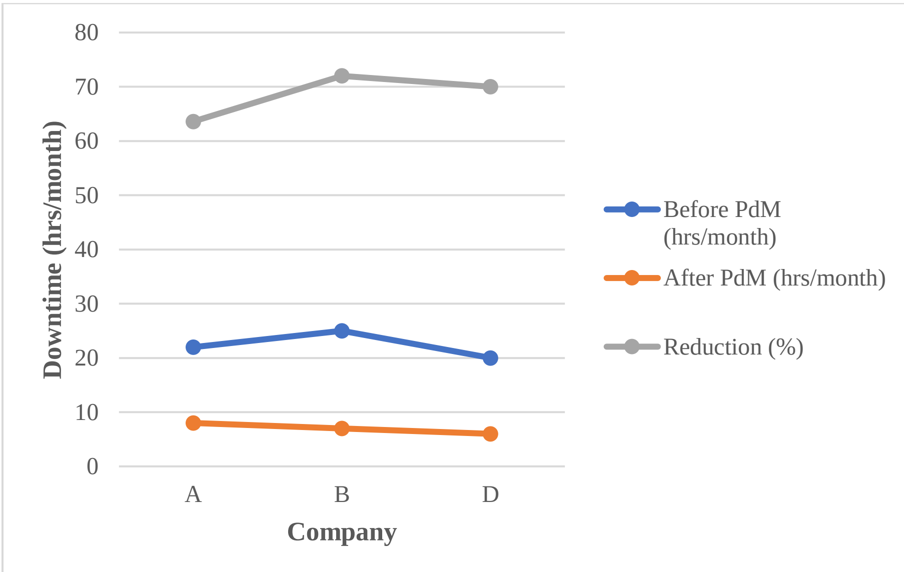

Figure 2: Downtime Before and After ML-PdM Implementation

Further performance trend is shown by the multi layer line chart. The third line which shows percentage reduction, is pared between 64% and 72% across the three firms, while the "Before PdM" lines start off high and drop steeply "After PdM". The visual evidence proves that PdM is valuable in maintaining constancy of production schedule and decreasing the incidence of disruptions.

The results reinforce further the acceptance of Hypothesis H1 and, in agreement with Hypothesis H1, ML-PdM reduces maintenance costs by means of operational continuity improvements.

4.3 Return on Investment (ROI) Analysis

In capital driven industries, adopting new technologies are justified via ROI. In this section, return on PdM implementation is compared by investment versus annual savings.

A summary of initial investments by companies in PdM systems, compared to annual savings developed through reduced downtime and increased efficiency, is provided in Table 3.

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Table 3: Investment in PdM Technology vs. ROI

Company	Initial Investment (INR Lakhs)	Annual Savings (INR Lakhs)	ROI (%)
A	15	40	166.7
B	18	52	188.9
D	12	36	200.0

Table 3 shows that all companies made back their investment within the first year with ROI from 166.7%-200%. Company D secured the best return by earning a ₹36 lakh savings from an investment of ₹12 lakh. Company B had a very nearly 189% return as well. Furthermore, even Company A, the one with the poorest savings, had an ROI of well over 166% which is pretty amazing by industry standards.

The percentage ROI for each company is presented in Figure 3 comparing four financial returns at various PdM investment scales.

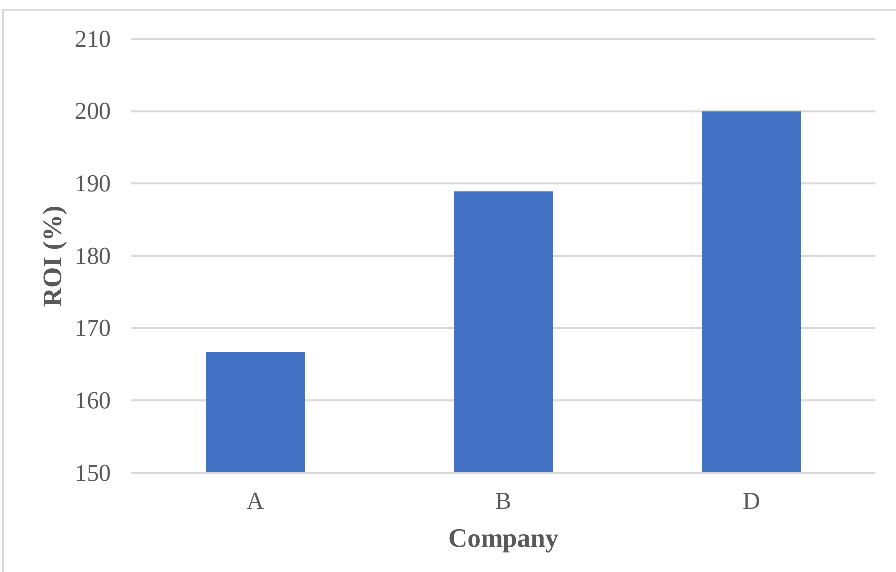

Figure 3: ROI from PdM Implementation

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As evident in the bar chart, these ROI results are shown, with Company D, B and A in that order. Thus, results indicate that PdM is both functionally effective and represent a profitable investment. Further validation of Hypothesis H1 is contributed by these financial metrics, in both efficiency and cost effectiveness.

4.4 Influence of Digital Infrastructure and Workforce Readiness

This subsection investigates the degree to which the existence of robust digital infrastructure and a skilled workforce significantly impacts the successful implementation of ML based predictive maintenance (ML PdM) systems. To understand if PdM adoption is determined by organizational readiness whether measured by human capital, technology or both.

Digital infrastructure and workforce skill scores (5 point scale) for six companies are shown in Table 4, along with a note of whether ML-PdM has been implemented.

Table 4: Infrastructure & Workforce Readiness Scores

Company	Digital Infra Score (out of 5)	Workforce Skill Score (out of 5)	PdM Implemented
A	4.5	4.2	Yes
B	4.8	4.6	Yes
C	2.1	2.5	No
D	4.3	4.4	Yes
E	2.3	2.6	No
F	2.0	2.3	No

The data shows that when PdM was implemented all companies had a digital infrastructure better than 4.0 and a workforce skill rating above 4.0. Specifically, scores of Company B were highest (4.8 and 4.6), Company A (4.5 and 4.2) and Company D (4.3 and 4.4). Non-adopters scored on

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infrastructure between 2.0 and 2.3 and on skills between 2.3 and 2.6. The relationship between organizational readiness for implementation and PdM success is striking in these findings.

On the basis of accepted hypothesis H2 which states that robust digital infrastructure and skilled workforce moderates the effectiveness of predictive maintenance systems, the research identifies the best predictive maintenance solution based on the following.

4.5 Strategic Implications and Alignment with Prior Research

Findings of the study corroborate that ML based Predictive Maintenance (PdM) helps to achieve increased operational efficiency, decrease downtime and high ROI in Indian manufacturing. The results from this research corroborate previous research, like Abidi et al. (2022) and Kalusivalingam et al. (2020) which found ML models can improve the performance of maintenance operations when integrated with IoT. Similar to other global case studies, observed downtime reductions exceed 63% and efficiency gains exceed 18%.

Importantly, it is shown in this study that digital infrastructure and skilled workforce are key enablers of successful PdM adoption which corroborates findings reported by Wadibhasme et al. (2024). In addition to the above, technological preparedness was underlined by the fact that only companies with readiness scores higher than 4.0 adopted PdM.

The results practically recommend that Indian manufacturers shall invest in training and smart infrastructure to take best out of PdM. The national programs like, 'Skill India' and 'Digital India' can have a key role in bridging capability gaps. This work has provided context specific insights for the maintenance in developing economies and endorsed the use of data driven approaches for the industrial maintenance decision making.

5. CONCLUSION AND RECOMMENDATIONS

This research presented and comprehensively investigated the application of machine learning (ML) in predictive maintenance (PdM) for Indian manufacturing in terms of technological feasibility, operational impact and strategic readiness. Detailed analysis allowed the research to fulfill all three stated objectives. It first examined the implementation landscape of ML-PdM systems across key manufacturing industries, including the primary algorithm types, data sources

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and IOT and cloud platform enabling technologies. Second, it evaluated the tangible benefits from PdM systems, of which by far the greatest was a concrete (up to 26%) improvement in operational efficiency and reduction (up to 72%) in machine downtime, finding that ML based maintenance strategies was vastly superior to traditional ones. Thirdly, it determined organizational enablers and constraints and found very strong correlations between PdM adoption and high levels of digital infrastructure and workforce preparedness. The findings of this study not only confirm that the objectives of the research had been achieved but also more fully explain the contextual dynamics of India’s industrial landscape. In summary, this work shows that ML- PdM is not such a technological revolution but a strategic lever to achieve sustainable, cost effective, smart manufacturing capabilities according with Industry 4.0 goals. Based on these results, actionable steps are proposed to support successful adoption and future scalability:

- PdM integration should be given the top priority by organizations to upgrade digital infrastructure and data systems to enable effective PdM.
- Unable to come to grips with ML tools and processes, it is important and necessary to invest tools and technologies in workforce training.
- Therefore, government and industry bodies should drive pilot-scale PdM adoption in SMEs to enable affordable and attractive technology adoption.

REFERENCES

1. Abidi, M. H., Mohammed, M. K., &Alkhalefah, H. (2022). Predictive maintenance planning for industry 4.0 using machine learning for sustainable manufacturing. *Sustainability*, *14*(6), 3387.
2. Alshahrani, N. (2024, December). Machine Learning Approaches for Predictive Maintenance in Industrial Operations. In *2024 IEEE 16th International Conference on Computational Intelligence and Communication Networks (CICN)* (pp. 365-372). IEEE.
3. Alshboul, O., Al Mamlook, R. E., Shehadeh, A., & Munir, T. (2024). Empirical exploration of predictive maintenance in concrete manufacturing: Harnessing machine

ISSN: 2320-3714
Volume:2 Issue:2
May 2025
Impact Factor:11.9
Subject: Management

learning for enhanced equipment reliability in construction project management. *Computers & Industrial Engineering*, *190*, 110046.

4. Carvalho, T. P., Soares, F. A., Vita, R., Francisco, R. D. P., Basto, J. P., & Alcalá, S. G. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering*, *137*, 106024.
5. Cinar, E., Kalay, S., &Saricicek, I. (2022). A predictive maintenance system design and implementation for intelligent manufacturing. *Machines*, *10*(11), 1006.
6. Çınar, Z. M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M., & Safaei, B. (2020). Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. *Sustainability*, *12*(19), 8211.
7. Florian, E., Sgarbossa, F., &Zennaro, I. (2021). Machine learning-based predictive maintenance: A cost-oriented model for implementation. *International Journal of Production Economics*, *236*, 108114.
8. Ghelani, D. (2024). Harnessing machine learning for predictive maintenance in energy infrastructure: A review of challenges and solutions. *International Journal of Science and Research Archive*, *12*(2), 1138-1156.
9. Hector, I., &Panjanathan, R. (2024). Predictive maintenance in Industry 4.0: A survey of planning models and machine learning techniques. *PeerJ Computer Science*, *10*, e2016.
10. Kalusivalingam, A. K., Sharma, A., Patel, N., & Singh, V. (2020). Enhancing Predictive Maintenance in Manufacturing Using Machine Learning Algorithms and IoT-Driven Data Analytics. *International Journal of AI and ML*, *1*(3).
11. Karuppusamy, P. (2021). Machine learning approach to predictive maintenance in manufacturing industry-a comparative study. *Journal of Soft Computing Paradigm*, *2*(4), 246-255.
12. Mahure, S. S., Deharkar, A., & Yadav, L. (2024). The Role of Machine Learning in Predictive Maintenance for Manufacturing Industries. *Int. J. Innov. Res. Sci. Eng. Technol.(IJIRSET)*, *13*, 7101-7106.
13. Rosati, R., Romeo, L., Cecchini, G., Tonetto, F., Viti, P., Mancini, A., &Frontoni, E. (2023). From knowledge-based to big data analytic model: a novel IoT and machine

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Impact Factor:11.9
Subject: Management

learning based decision support system for predictive maintenance in Industry 4.0. *Journal of Intelligent Manufacturing*, *34*(1), 107-121.

14. Subhashini, S. J., Basha, S. A., Rao, B. S., Gayathri, S., &Mangrulkar, A. (2025). Machine Learning-Based Predictive Maintenance: Enhancing Industrial Reliability through Data-Driven Approaches. *Journal of Marketing & Social Research*, *2*, 373-383.
15. Wadibhasme, R. N., Naresh, M., Vikram, G., VV, A. S., &Jermina, F. (2024, August). Utilizing Machine Learning Techniques for Enhanced Predictive Maintenance in the Manufacturing Sector. In *2024 2nd International Conference on Networking, Embedded and Wireless Systems (ICNEWS)* (pp. 1-6). IEEE.

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