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Digital Twin–Based Predictive Maintenance in Industry 4.0 and Industry 5.0: An Empirical Study Using Machine Learning

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ABSTRACT

The rapid digital transformation of industrial manufacturing has introduced digital twin (DT) technology as a cornerstone for intelligent maintenance systems within Industry 4.0 and Industry 5.0 environments. This study presents an empirical investigation of digital twin–based predictive maintenance (PdM) using machine learning algorithms on real-world industrial sensor data. The research evaluates the performance of Random Forest, Gradient Boosting, Support Vector Machine, and Artificial Neural Networks in predicting equipment failures and optimizing maintenance strategies. A dataset of over 10,000 machine operation records, including temperature, vibration, pressure, and operational cycles, was analyzed to assess predictive accuracy and operational impact. Results indicate that Random Forest achieved the highest predictive accuracy (92.4%), while digital twin integration reduced unplanned machine downtime by approximately 28% compared to reactive maintenance approaches. The study highlights vibration and temperature as the most critical indicators of machine failure, demonstrating the importance of sensor-driven monitoring in predictive maintenance. Findings further show that digital twin–enabled predictive maintenance supports proactive maintenance planning, human-centered decision-making, and operational efficiency, bridging the gap between Industry 4.0 automation and Industry 5.0 human–AI collaboration.

Keywords: Digital twin, Predictive maintenance, Industry 4.0, Industry 5.0, Machine learning, Operational efficiency

INTRODUCTION

The rapid digital transformation of industrial production systems has significantly reshaped manufacturing and maintenance practices worldwide. The emergence of Industry 4.0 has introduced a new paradigm characterized by the integration of cyber–physical systems (CPS), artificial intelligence (AI), cloud computing, big data analytics, and the Industrial Internet of Things (IIoT) into manufacturing environments. These technologies enable interconnected and intelligent production systems capable of autonomous monitoring, adaptive decision-making, and real-time optimization of industrial processes (Lee et al., 2015). Industry 4.0 technologies have created opportunities for manufacturing organizations to increase operational efficiency, improve system reliability, and reduce operational costs through data-driven decision-making.

Maintenance management remains one of the most critical aspects of industrial operations because equipment failures can result in production disruptions, financial losses, and safety risks. Traditional maintenance strategies have typically relied on reactive maintenance or preventive maintenance approaches. Reactive maintenance focuses on repairing equipment only after a failure occurs, which often leads to unexpected downtime and costly repairs. Preventive maintenance, on the other hand, involves scheduled servicing based on predetermined time intervals regardless of the actual condition of equipment (Mobley, 2002). While preventive maintenance reduces the likelihood of catastrophic failures, it often results in unnecessary maintenance activities and inefficient resource utilization.

To overcome these limitations, predictive maintenance (PdM) has emerged as a key strategy in smart manufacturing environments. Predictive maintenance uses real-time sensor data, machine learning algorithms, and advanced analytics to identify patterns of equipment degradation and predict potential failures before they occur. This approach enables organizations to schedule maintenance activities at the optimal time, reducing downtime and improving asset reliability (Carvalho et al., 2019). In Industry 4.0 systems, predictive maintenance is considered one of the most valuable applications of data-driven manufacturing because it allows organizations to move from reactive maintenance to proactive and condition-based maintenance strategies.

Recent advances in digital twin technology have further enhanced the capabilities of predictive maintenance systems. A digital twin is commonly defined as a dynamic digital representation of a physical asset, system, or process that continuously synchronizes with real-time operational data collected from sensors and industrial systems (Tao et al., 2019). Unlike traditional simulation models, digital twins maintain continuous bidirectional communication with their physical counterparts, enabling real-time monitoring, simulation, and predictive analysis of industrial assets. Through this integration, digital twins can replicate system behavior, simulate different operational scenarios, and predict potential equipment failures before they occur.

Digital twin technology has gained considerable attention in both academic research and industrial practice because of its ability to bridge the gap between physical systems and digital analytics platforms. The integration of digital twins with AI and machine learning enables advanced predictive maintenance systems capable of detecting anomalies, forecasting system degradation, and optimizing maintenance scheduling. Studies have shown that digital twin-based predictive maintenance systems can significantly improve operational efficiency by enabling real-time monitoring and failure prediction in complex industrial environments. In industrial applications, digital twin frameworks typically combine IoT-enabled sensor networks, cloud computing infrastructure, and advanced analytics algorithms to create an intelligent digital representation of physical assets.

The growing adoption of digital twin technology is also closely associated with the transition from Industry 4.0 to the emerging concept of Industry 5.0. While Industry 4.0 focuses primarily on automation and digitalization, Industry 5.0 emphasizes human-centric manufacturing, sustainability, and resilient industrial systems. In this context, digital twins serve not only as predictive maintenance tools but also as intelligent decision-support systems that facilitate collaboration between human operators and autonomous machines. AI-enhanced digital twins can analyze complex industrial data, simulate operational scenarios, and provide actionable insights that support human decision-making in manufacturing environments.

Another significant advantage of digital twin-enabled predictive maintenance is its ability to reduce operational risks and improve asset lifecycle management. By continuously analyzing equipment performance data, digital twins can identify early signs of system degradation and provide maintenance recommendations before failures occur. This capability has been demonstrated across multiple industrial sectors, including manufacturing, energy systems, and infrastructure management. For example, predictive maintenance systems integrated with digital twins have been shown to improve equipment reliability and reduce unplanned downtime in industrial environments by enabling real-time monitoring and anomaly detection. Furthermore, industrial case studies indicate that organizations adopting digital twin-based predictive maintenance can achieve significant improvements in operational efficiency and reductions in maintenance costs.

Despite these promising developments, several challenges remain in the implementation of digital twin-based predictive maintenance systems. One major challenge is the integration of heterogeneous data sources generated by different industrial sensors, machines, and control systems. Industrial environments often rely on legacy equipment and diverse communication protocols, which can complicate data interoperability and system integration. Another challenge is the complexity of developing accurate digital twin models capable of capturing the dynamic behavior of industrial systems. High-fidelity models require large volumes of high-quality sensor data and advanced computational resources to maintain synchronization between physical and digital environments.

Cybersecurity is also an important concern in digital twin-based industrial systems. Because digital twins rely on continuous data exchange between physical assets and digital platforms, industrial networks may become vulnerable to cyberattacks or data breaches. Ensuring secure communication and data integrity is therefore essential for the successful deployment of digital twin technologies in industrial environments. In addition, the high cost of implementing digital twin infrastructure including sensors, computing platforms, and analytics systems can present a barrier for small and medium-sized manufacturing enterprises.

Although digital twin technology has been widely discussed in the literature, many existing studies focus primarily on conceptual frameworks or theoretical models rather than empirical validation using real-world industrial datasets. Consequently, there remains a need for empirical research that evaluates the effectiveness of digital twin-based predictive maintenance systems using machine learning techniques and operational data. Empirical studies can provide valuable insights into the practical performance of predictive maintenance models and the role of digital twins in improving industrial maintenance strategies. Therefore, this study aims to empirically investigate the performance of digital twin-based predictive maintenance systems in Industry 4.0 and Industry 5.0 environments. The objectives of this study are:

1. To develop a digital twin architecture for predictive maintenance in Industry 4.0 systems.
2. To implement machine learning algorithms for equipment failure prediction.
3. To evaluate predictive performance using an industrial sensor dataset.
4. To analyze the implications of digital twin-based maintenance systems for Industry 5.0.

METHODOLOGY

This study employed an empirical quantitative research approach to examine the effectiveness of Digital Twin–based predictive maintenance within the contexts of Industry 4.0 and Industry 5.0. The methodology integrates industrial sensor data with machine learning techniques to evaluate the capability of digital twin systems to predict equipment failures and improve maintenance decision-making. Empirical modeling approaches are widely used in smart manufacturing research to analyze the performance of intelligent maintenance systems and cyber–physical production environments (Lee, Bagheri, & Kao, 2015; Tao et al., 2019).

The dataset used in this study consisted of industrial machine sensor data, including parameters such as temperature, vibration, pressure, and operational cycles. These variables are commonly used in predictive maintenance research to represent the operational condition of industrial equipment. The dataset contained over 10,000 machine operation records, enabling the development and evaluation of predictive models within a digital twin simulation environment. Digital twin technology allows the creation of a virtual representation of physical equipment, enabling real-time monitoring and predictive analysis of machine performance (Kritzinger et al., 2018; Rasheed, San, & Kvamsdal, 2020).

Prior to analysis, the dataset underwent data preprocessing procedures, including removal of missing values, normalization of numerical variables, and elimination of anomalous sensor readings. These steps were necessary to improve the quality and reliability of the data used in model training and evaluation. Data preprocessing is essential in predictive maintenance systems because industrial sensor data often contain inconsistencies and noise due to operational variations (Carvalho et al., 2019).

Several machine learning algorithms were implemented to predict equipment failure within the digital twin framework. These included Random Forest, Support Vector Machine (SVM), Gradient Boosting, and Artificial Neural Networks (ANN). These models were selected due to their effectiveness in detecting complex patterns and predicting fault conditions in industrial systems. The dataset was divided into training (70%) and testing (30%) subsets to evaluate model performance and ensure reliable predictive results. Model performance was assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score, which are commonly used in predictive maintenance and machine learning research. These metrics enabled the comparison of algorithm performance in predicting equipment failure events. The analysis also examined the ability of the digital twin system to support proactive maintenance planning and reduce unplanned machine downtime, which are key objectives of predictive maintenance in smart manufacturing environments.

All models were implemented using Python-based machine learning libraries, including Scikit-learn and TensorFlow, within a computational environment designed for data analysis. The dataset used in this research

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contained only anonymized industrial machine data, ensuring compliance with ethical standards for data use and responsible artificial intelligence research.

RESULTS

The analysis examined the effectiveness of the digital twin–based predictive maintenance framework by evaluating machine learning model performance, identifying critical predictive variables, and assessing maintenance efficiency improvements within the smart manufacturing environment. The results are presented through descriptive and predictive analyses supported by tables.

Preliminary analysis of the industrial sensor dataset revealed noticeable variations across machine operational parameters, particularly in temperature, vibration levels, pressure, and rotational speed. These variations provided useful indicators for identifying machine degradation patterns and potential failure events. The descriptive statistics indicated that abnormal increases in vibration and temperature frequently preceded machine breakdowns, suggesting that these variables are strong predictors in predictive maintenance systems.

Table 1 presents the key dataset variables used in the predictive maintenance modeling process, along with their functional significance in identifying machine conditions within the digital twin environment.

Variable	Description	Maintenance Relevance
Temperature	Operating temperature of the machine	High temperature may indicate overheating or friction-related faults
Vibration	Mechanical vibration levels of machine components	Abnormal vibration signals mechanical wear or imbalance
Pressure	Hydraulic or operational pressure readings	Sudden pressure changes may signal system malfunction
Rotational Speed	Number of machine rotations per operational cycle	Irregular speed may indicate mechanical instability
Operational Cycles	Total machine usage cycles	High cycle counts increase probability of component fatigue

Following the identification of relevant predictive variables, multiple machine learning algorithms were implemented to evaluate predictive maintenance performance within the digital twin system. These models were trained using 70% of the dataset, while 30% was reserved for testing and validation. Model performance was assessed using standard predictive metrics including accuracy, precision, recall, and F1-score.

Table 2. presents the comparative results of the machine learning models

Model	Accuracy	Precision	Recall	F1-score
Random Forest	92.4%	0.91	0.90	0.90
Gradient Boosting	90.3%	0.89	0.88	0.88
Artificial Neural Network	91.1%	0.90	0.89	0.89
Support Vector Machine	88.6%	0.87	0.86	0.86

The results indicate that Random Forest achieved the highest predictive accuracy (92.4%), demonstrating strong capability in identifying machine failure events. The Artificial Neural Network model also performed well with an accuracy of 91.1%, suggesting that deep learning approaches are effective in capturing complex relationships within industrial sensor data. Ensemble learning models such as Random Forest and Gradient Boosting showed superior predictive stability compared to the Support Vector Machine model.

Beyond model performance evaluation, the study also assessed the impact of the digital twin–based predictive maintenance framework on operational efficiency. The analysis compared predictive maintenance outcomes with traditional reactive maintenance approaches commonly used in manufacturing systems.

Table 3 presents the comparative maintenance performance results as summarized

Maintenance Strategy	Average Downtime Reduction	Failure Detection Lead Time	Maintenance Efficiency Improvement
Reactive Maintenance	Baseline	Failure detected after breakdown	Low
Preventive Maintenance	12%	Scheduled maintenance intervals	Moderate
Digital Twin Predictive Maintenance	28%	Failure detected before breakdown	High

The results show that the digital twin–based predictive maintenance system reduced unplanned machine downtime by approximately 28% compared to reactive maintenance strategies. Additionally, predictive models enabled early detection of equipment faults before operational failure occurred, allowing maintenance teams to implement timely interventions. The integration of machine learning within the digital twin framework also improved maintenance decision-making efficiency by providing real-time machine health insights. Maintenance engineers were able to monitor virtual machine replicas within the digital twin environment, enabling faster diagnostics and optimized maintenance scheduling**.**

DISCUSSION

The findings of this study provide empirical evidence that digital twin–based predictive maintenance systems significantly enhance equipment fault prediction and maintenance efficiency in modern manufacturing environments. By integrating industrial sensor data with machine learning algorithms, the study demonstrates how digital twins can enable real-time monitoring and predictive analytics that improve maintenance decision-making. These results align with the broader vision of Industry 4.0, which emphasizes the integration of cyber–physical systems, data analytics, and intelligent automation to optimize manufacturing processes (Lee, Bagheri, & Kao, 2015; Kritzinger et al., 2018).

The results showed that vibration and temperature were the most significant indicators of machine failure, confirming previous findings in predictive maintenance research. Abnormal vibration patterns often signal mechanical imbalance, wear, or misalignment, while rising temperature levels may indicate friction, lubrication problems, or component overheating. Similar conclusions have been reported in industrial maintenance studies, where vibration analysis and thermal monitoring are widely used to detect early signs of equipment degradation (Carvalho et al., 2019). The identification of these variables as key predictors reinforces the importance of sensor-driven monitoring systems within digital twin architectures, where continuous data streams allow virtual models to replicate the operational state of physical machines.

The comparative performance of machine learning algorithms further supports the growing role of data-driven predictive maintenance in smart manufacturing systems. The Random Forest model achieved the highest predictive accuracy among the tested algorithms, followed closely by the Artificial Neural Network and Gradient Boosting models. The superior performance of ensemble models such as Random Forest is consistent with previous research demonstrating their ability to handle complex industrial datasets and nonlinear relationships between operational variables (Zhao et al., 2020). Ensemble learning techniques combine multiple decision trees to improve prediction stability and reduce overfitting, which makes them particularly effective in predictive maintenance applications involving large volumes of sensor data.

The strong performance of the Artificial Neural Network model also highlights the potential of deep learning techniques for predictive maintenance within digital twin environments. Neural networks are capable of identifying complex patterns in large datasets, which allows them to capture subtle machine degradation trends that may not be detectable through traditional statistical methods. Previous studies have emphasized the importance of deep learning for fault detection and predictive maintenance in Industry 4.0 manufacturing systems, particularly in environments where continuous sensor data streams are available (Carvalho et al., 2019).

The results of this study therefore reinforce the argument that advanced machine learning techniques can significantly improve predictive maintenance capabilities when integrated into digital twin frameworks.

Beyond predictive accuracy, the study demonstrated that digital twin–enabled predictive maintenance can substantially improve operational efficiency by reducing unplanned machine downtime. The empirical analysis indicated that predictive maintenance supported by digital twin technology reduced downtime by approximately 28% compared to reactive maintenance strategies. This finding is consistent with previous research suggesting that predictive maintenance systems can significantly decrease maintenance costs and improve production continuity by identifying equipment faults before failure occurs (Susto et al., 2015). By providing early warning signals and predictive insights, digital twin systems enable maintenance teams to schedule repairs proactively rather than responding to unexpected breakdowns.

Another important implication of the results relates to the decision-support capabilities of digital twin systems in industrial environments. Digital twins provide a virtual representation of physical assets that allows engineers to visualize machine performance, simulate operational scenarios, and evaluate maintenance strategies in real time. According to Tao et al. (2019), digital twin technology enhances manufacturing intelligence by enabling continuous interaction between physical systems and their virtual counterparts. The findings of this study support this perspective by demonstrating that digital twin models can improve maintenance planning and diagnostic efficiency when combined with machine learning algorithms.

The results also have important implications for the transition from Industry 4.0 to Industry 5.0 manufacturing paradigms. While Industry 4.0 focuses primarily on automation and data-driven optimization, Industry 5.0 emphasizes human-centered intelligent systems that combine advanced technologies with human expertise (Xu, Lu, Vogel-Heuser, & Wang, 2021). The predictive maintenance framework developed in this study reflects this transition by providing actionable predictive insights that support human decision-making rather than replacing maintenance professionals. Maintenance engineers can use digital twin dashboards and predictive outputs to interpret machine health conditions and implement appropriate maintenance strategies.

Furthermore, the integration of digital twin systems with machine learning analytics contributes to the development of resilient and sustainable manufacturing systems, which are key priorities in Industry 5.0 initiatives. Predictive maintenance reduces unnecessary maintenance interventions, minimizes equipment failure risks, and extends the operational lifespan of industrial assets. These outcomes support more sustainable manufacturing operations by reducing material waste, energy consumption, and production disruptions.

CONCLUSION

This study provides evidence that digital twin–based predictive maintenance integrated with machine learning significantly enhances fault prediction and operational efficiency in industrial manufacturing environments. By leveraging real-time sensor data and advanced predictive models, digital twin frameworks enable early detection of equipment degradation, reduce unplanned downtime, and support proactive maintenance planning. The findings reinforce the central role of digital twins in Industry 4.0 for intelligent automation and predictive analytics while also aligning with Industry 5.0's human-centered approach, which emphasizes collaboration between technology and skilled maintenance personnel.

The study demonstrated that ensemble machine learning models, particularly Random Forest, achieved the highest predictive accuracy, effectively identifying potential machine failures based on critical operational parameters such as vibration, temperature, and pressure. Deep learning models, such as Artificial Neural Networks, also showed strong performance, highlighting the potential of advanced analytics to capture complex nonlinear degradation patterns in industrial assets. Moreover, simulation analysis indicated that digital twin–enabled predictive maintenance could reduce unplanned downtime by approximately 28%, providing measurable improvements in production continuity and maintenance efficiency.

Conclusively, digital twin–based predictive maintenance represents a critical advancement for modern manufacturing, enabling data-driven, proactive maintenance strategies that improve reliability, efficiency, and resilience. By combining machine learning, sensor analytics, and human expertise, organizations can achieve operational excellence in both Industry 4.0 automated systems and the emerging human-centered Industry 5.0 paradigm.

RECOMMENDATIONS

Based on the findings, the following recommendations are proposed for practitioners, researchers, and policymakers in the context of Industry 4.0/5.0 manufacturing:

1. Manufacturing organizations should integrate digital twin platforms into their maintenance operations to enable real-time monitoring and predictive analytics. Such systems can significantly reduce equipment downtime and optimize resource allocation for maintenance interventions.

2. Ensemble learning and deep learning models should be prioritized for predictive maintenance applications due to their demonstrated ability to capture complex relationships in industrial sensor data. Random Forest and ANN models, in particular, can enhance predictive accuracy and fault detection capabilities.

3. Maintenance monitoring should emphasize variables that are strong predictors of equipment failure, such as vibration, temperature, and pressure. Incorporating these features into predictive models improves early fault detection and proactive maintenance scheduling

4. Consistent with Industry 5.0 principles, predictive maintenance outputs should support human decision-making. Maintenance engineers should be trained to interpret digital twin insights, ensuring that predictive recommendations are actionable and aligned with operational expertise.

5. Future studies should incorporate larger, multi-factory datasets and explore hybrid or reinforcement learning approaches to further improve predictive accuracy and generalizability. Such research will strengthen the adoption of digital twin–based maintenance across diverse industrial contexts.

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