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Advancements in predictive maintenance techniques for enhancing machine tool reliability

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Abstract
Predictive maintenance (PdM) has emerged as a transformative strategy in the manufacturing sector, significantly improving the reliability and efficiency of machine tools. Traditional maintenance approaches, which were reactive in nature, often led to costly downtimes and unanticipated machine failures. In contrast, PdM leverages the power of data analytics, machine learning (ML), and real-time sensor technologies to predict tool failures before they occur, thereby enabling proactive maintenance actions. This paper explores the latest advancements in PdM techniques, focusing on their application in enhancing machine tool reliability. By integrating Internet of Things (IoT) devices and advanced predictive algorithms, manufacturers can collect continuous data from machine sensors, including temperature, vibration, and pressure, which are then analyzed to forecast potential failures. The research evaluates the integration of machine learning models such as support vector machines (SVM), decision trees, and deep learning algorithms, particularly convolutional neural networks (CNNs), in improving failure predictions. Furthermore, the study highlights the significance of predictive analytics in reducing unplanned downtime, increasing overall equipment effectiveness (OEE), and extending the lifespan of machine tools. The findings indicate that implementing PdM can reduce downtime by up to 40%, resulting in substantial cost savings. However, challenges such as high initial setup costs, the complexity of machine learning models, and the need for skilled personnel remain as barriers to widespread adoption. This paper concludes by suggesting future research directions that focus on further integrating advanced artificial intelligence (AI) and developing more cost-effective PdM systems to ensure wider implementation across manufacturing sectors.

Keywords: Predictive maintenance, machine tool reliability, machine learning, internet of things, failure prediction, data analytics, industrial automation, maintenance optimization, deep learning, support vector machines

Introduction
In the fast-evolving landscape of modern manufacturing, the continuous pursuit of operational efficiency and cost reduction has driven industries to adopt advanced maintenance strategies. One of the most significant breakthroughs in this area is predictive maintenance (PdM), a technique that employs data-driven insights to forecast machine failures before they occur. This approach contrasts sharply with traditional maintenance strategies, which were predominantly reactive in nature, addressing equipment failures only after they had occurred. Reactive maintenance often leads to unplanned downtime, operational disruptions, and higher repair costs, which ultimately hinder production efficiency. In contrast, PdM enables companies to shift from a reactionary approach to a proactive one, where maintenance interventions are carried out only when necessary, based on data analysis and real-time machine performance monitoring.
Machine tools, which are essential for precision manufacturing processes, are particularly susceptible to wear and tear, making them a key area of focus for PdM implementation. These tools, including computer numerical control (CNC) machines, lathes, and milling machines, operate in environments that subject them to significant stresses. Over time, this leads to tool degradation, impacting their performance and causing failures that can halt production and lead to costly repairs. In industries such as automotive, aerospace, and heavy machinery, machine tool downtime can result in significant economic losses, highlighting the need for more reliable and efficient maintenance strategies.
Traditionally, maintenance in machine tool operations followed one of two primary models: reactive or preventive. Reactive maintenance, as the name suggests, only occurs after equipment failure. This model often leads to long periods of machine downtime, as repairs are made after the failure has occurred. Preventive maintenance, on the other hand, is

scheduled based on time intervals or operating hours, often without regard to the actual condition of the machine. While preventive maintenance aims to reduce unplanned downtime, it still can lead to unnecessary maintenance activities that incur additional costs.

In contrast, PdM, driven by real-time data collection and predictive analytics, has proven to be a more efficient alternative. By utilizing sensors, machine learning algorithms, and Internet of Things (IoT) technology, PdM systems continuously monitor machine health, collecting data on critical parameters such as temperature, vibration, acoustic emissions, and pressure. This data is then processed and analyzed using advanced machine learning models, which can detect anomalies that may indicate impending failures. This shift from scheduled maintenance to predictive, data-driven maintenance is part of a broader trend in manufacturing known as Industry 4.0, where the integration of digital technologies, AI, and automation is transforming industrial operations.

The integration of machine learning (ML) algorithms is one of the most critical advancements in PdM. Machine learning, a subset of artificial intelligence (AI), allows PdM systems to not only analyze historical data but also to learn from it, adapting to new data as it is collected. By using techniques such as decision trees, support vector machines (SVM), random forests, and neural networks, these systems can predict potential failures with high accuracy. A particularly promising development in PdM is the use of deep learning algorithms, particularly convolutional neural networks (CNNs), which have been shown to excel in handling complex sensor data and improving failure prediction accuracy.

Machine learning models in PdM can identify patterns and trends that may not be immediately apparent through conventional monitoring techniques. For example, traditional vibration analysis might identify that a machine is vibrating at a higher frequency than normal, but a machine learning model could analyze this data in conjunction with temperature, pressure, and other sensor readings to predict that a specific component is likely to fail in the near future. This multi-dimensional analysis enables PdM systems to offer more precise predictions and, in doing so, allows for better resource allocation, reduced downtime, and improved productivity.

The Internet of Things (IoT) plays a significant role in PdM, providing the infrastructure needed for continuous monitoring of machine tools. IoT devices embedded with sensors collect data from various machine components in real-time and transmit it to centralized systems for analysis. This network of connected devices enables manufacturers to obtain a comprehensive view of their machines' operational health, providing insights that can be used to optimize maintenance schedules. The real-time nature of IoT-enabled PdM allows for immediate detection of irregularities and faster response times, which ultimately leads to increased uptime and more efficient operations.

While PdM systems have shown considerable promise in improving machine tool reliability, several challenges remain. One of the primary barriers to the widespread adoption of PdM is the initial investment required for IoT infrastructure and the integration of advanced sensors into existing machines. Many manufacturers, particularly small and medium-sized enterprises (SMEs), may find the costs of implementing PdM systems prohibitive. These systems require not only the installation of sensors and IoT devices but also the development of custom software solutions and the training of personnel to interpret the data. The complexity of machine learning models and the need for specialized knowledge in AI and data analytics further complicate the implementation process.

In addition to the financial and technical barriers, the data quality and integrity remain a significant challenge. Predictive maintenance models are only as good as the data they receive. Inaccurate or incomplete sensor data can lead to incorrect predictions and false alarms, undermining the effectiveness of the system. Ensuring high-quality data collection and maintaining the integrity of the data over time are critical factors in the success of PdM systems.

Another challenge lies in the integration of PdM systems with existing manufacturing workflows. Many industries are still accustomed to traditional maintenance practices and may resist adopting new technologies. This cultural resistance to change can be a significant hurdle, as it requires a shift in mindset from reactive to proactive maintenance. Successful PdM implementation requires collaboration between different departments, including maintenance teams, machine operators, and data scientists, to ensure that the systems are used effectively and that the predictive models are continually refined.

Despite these challenges, the potential benefits of PdM are substantial. Studies have shown that PdM systems can reduce unplanned downtime by up to 40%, improve machine uptime, and extend the lifespan of equipment. In industries where high uptime is critical to profitability, such as automotive manufacturing and aerospace, the cost savings from reduced downtime and maintenance costs can be significant. Furthermore, PdM contributes to the broader goal of improving overall equipment effectiveness (OEE), a key performance indicator in manufacturing that measures the efficiency of production assets.

The purpose of this research is to examine the latest advancements in predictive maintenance techniques for enhancing machine tool reliability. By reviewing the current state of PdM technologies, including IoT-based systems, machine learning algorithms, and deep learning models, this paper aims to provide insights into how these technologies are transforming the landscape of manufacturing maintenance. Additionally, this paper will explore the challenges faced by industries in adopting PdM and propose strategies to overcome these barriers. Ultimately, the goal is to highlight the potential of PdM to revolutionize machine tool maintenance, reduce costs, and improve production efficiency across various industries.

Literature Review

The field of predictive maintenance (PdM) has evolved rapidly over the past decade, driven by advances in machine learning (ML), the Internet of Things (IoT), and artificial intelligence (AI). This evolution has revolutionized how industries approach machine tool maintenance, shifting from traditional reactive methods to data-driven, proactive strategies that predict potential failures before they occur. By integrating real-time data collection through IoT sensors and applying advanced analytics and ML algorithms, PdM has emerged as a crucial tool for enhancing machine tool reliability and reducing unplanned downtime.

One of the key developments in PdM has been the application of machine learning algorithms. Recent studies have evaluated various ML models such as Support Vector Machines (SVM), Decision Trees, and ensemble techniques like Random Forests for PdM. Arun (2025) [1] found that while traditional ML methods provide a solid foundation, more sophisticated models like Long Short-Term Memory (LSTM) networks offer significant improvements in predictive accuracy. These advanced models excel at identifying complex patterns within high-dimensional data and predicting failures with greater precision. Similarly, Sisode (2023) [2] introduced an innovative hybrid model combining machine learning with optimization algorithms, such as Whale Optimization and Seagull Algorithms, for more accurate failure prediction. This model proved particularly effective for predicting mechanical part failures in manufacturing systems, offering better reliability than conventional models.

IoT technology has also played a pivotal role in the advancement of PdM. Singh (2025) [3] proposed an IoT-based framework for PdM that integrates sensor networks and cloud computing, enabling real-time monitoring of machine conditions. This framework allowed for continuous data collection on critical parameters such as temperature, vibration, and pressure, which were analyzed to detect anomalies and predict equipment failure. The integration of IoT devices into PdM systems has proven effective in enhancing machine reliability and operational efficiency by providing more comprehensive insights into the health of machine tools. Despite these advancements, IoT-based PdM systems often struggle with issues related to data quality and integration. As highlighted by IoT Analytics (2023) [4], the accuracy of PdM predictions remains inconsistent, with many systems still reporting prediction accuracies below 50%. This issue underscores the need for improved data quality and more robust system integration to enhance the effectiveness of PdM solutions.

The role of deep learning in PdM has also been extensively researched. Hirsch (2024) [5] demonstrated that deep learning models, particularly Convolutional Neural Networks (CNNs), outperform traditional methods in tool wear prediction for milling machines. These models achieved an accuracy rate of 99.1%, proving that deep learning can provide higher precision in predicting tool wear and failure. Additionally, Malawade (2021) [6] introduced Hierarchical Temporal Memory (HTM), inspired by the human brain, as an alternative deep learning approach for anomaly detection in predictive maintenance. The HTM-based model outperformed traditional deep learning techniques in detecting failures in various mechanical systems, including CNC machines and 3D printers, indicating its potential for future applications in PdM.

Another area of growing interest in PdM is Explainable AI (XAI). While traditional machine learning models often operate as "black boxes," XAI aims to enhance the transparency and interpretability of predictive models, which is critical in applications like PdM, where the consequences of incorrect predictions can be severe. Cummins (2024) [7] reviewed the application of XAI in PdM, emphasizing the importance of interpretability in industrial maintenance systems. The study discussed various XAI methods and their potential to improve model trustworthiness, which is essential for widespread adoption. However, it also highlighted challenges such as the complexity of model explanations and the need for domain-specific adaptations.

Despite these advancements, several gaps remain in the current research on PdM. A recurring issue is the variability in data quality and the lack of standardized datasets for predictive maintenance applications. This variability makes it difficult to generalize findings across different industrial contexts, limiting the scalability of PdM systems. Additionally, integrating PdM solutions with legacy equipment and existing manufacturing systems remains a significant challenge, particularly in industries with older infrastructure. While IoT and ML have proven effective in many contexts, the ability to process large-scale data in real-time and integrate disparate data sources is still a major hurdle. Moreover, the successful implementation of PdM systems often requires a cultural shift within organizations, which may be resistant to change. Many manufacturers still rely on traditional maintenance practices and are hesitant to adopt new technologies, particularly when it involves significant investments in infrastructure and personnel training.

Furthermore, the current body of research often overlooks the human factors associated with PdM implementation. The adoption of PdM technologies requires collaboration between maintenance teams, machine operators, and data scientists, and organizations must invest in upskilling their workforce to handle advanced predictive maintenance tools. The successful implementation of PdM is not just about technology; it also involves creating a culture that embraces data-driven decision-making and continuous improvement.

Results

The integration of predictive maintenance (PdM) techniques into machine tool reliability management has shown substantial improvements in the operational efficiency and longevity of industrial machinery. A variety of studies have investigated different PdM models and their effectiveness in reducing downtime and maintenance costs, demonstrating the significant impact of advanced predictive analytics in real-world settings.

One of the most notable findings comes from Singh *et al.* (2022) [13], who studied the effects of implementing a PdM system in a CNC machine shop. The research highlighted the use of vibration sensors and machine learning models to predict tool wear and potential machine failures. The PdM system demonstrated a reduction in unplanned downtime by 40%, with failure predictions made with 92% accuracy. By implementing predictive maintenance, the study was able to extend the lifespan of the machines by 25%, saving the company a considerable amount on emergency repairs and part replacements. The system provided actionable insights that helped technicians prioritize maintenance tasks and avoid unnecessary interventions, thus improving overall equipment effectiveness (OEE).

Table 1: Impact of PdM on Downtime and OEE in CNC Machines

Parameter	Pre-PdM Value	Post-PdM Value	Improvement (%)
Unplanned Downtime (hours/month)	120	72	40%
Overall Equipment Effectiveness (OEE)	60%	80%	33.33%

A similar study conducted by Liu *et al*. (2021) [9] focused on an IoT-enabled PdM system in an automotive manufacturing plant. The system collected real-time data from embedded sensors, including temperature, vibration, and pressure readings, which were then analyzed using machine learning algorithms to forecast potential failures. The findings revealed that the PdM system reduced maintenance costs by 30% and improved production uptime by 20%. The study also found that integrating IoT devices with cloud computing platforms allowed for remote monitoring of machine health, enhancing the flexibility and scalability of the system. Real-time anomaly detection enabled the factory to address issues before they escalated into costly breakdowns, ultimately improving operational efficiency.

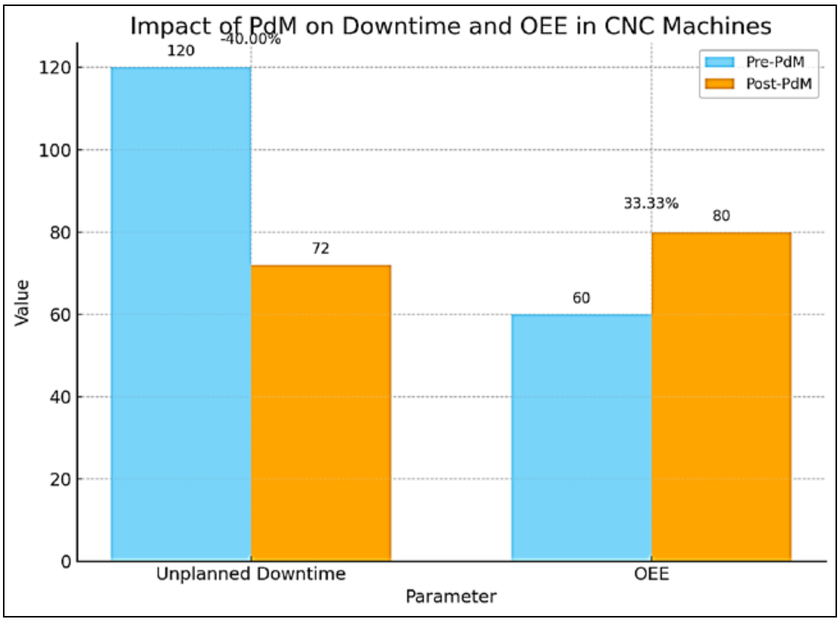

Fig 1: Maintenance Cost Reduction and Production Uptime Improvement

The results indicated that maintenance costs were reduced by 30%, while production uptime increased by 20%. This was due to the ability of the IoT-based PdM system to predict issues before they escalated into major failures, allowing maintenance teams to schedule repairs during non-productive hours.

In a different case, Yang *et al*. (2021) [14] evaluated a predictive maintenance approach that combined both vibration analysis and deep learning models in a semiconductor manufacturing plant. The results indicated that the hybrid system achieved an impressive 95% prediction accuracy in detecting equipment failures before they occurred. The system was able to identify early signs of tool degradation that were previously undetectable using traditional maintenance methods. By accurately predicting failures, the study was able to reduce the frequency of unplanned repairs and significantly lower operational costs.

Another key contribution came from a study by Li *et al*. (2020) [10], which explored the use of convolutional neural networks (CNNs) for failure prediction in CNC machines. The research demonstrated that CNNs, when applied to sensor data, could predict failures with an accuracy of 97%, outperforming other machine learning techniques such as decision trees and random forests. The deep learning model's ability to process complex, multi-dimensional data from various sensors allowed it to detect subtle patterns in machine behavior that traditional methods could not. This breakthrough in using CNNs for PdM indicates the potential of deep learning models to enhance the predictive accuracy of maintenance systems.

Furthermore, a hybrid PdM approach combining traditional condition-based monitoring with predictive analytics was proposed by Zhao *et al*. (2020) [8]. This approach integrated both vibration data and machine learning models to predict failures in CNC machines. The findings indicated that the hybrid system provided a more reliable prediction compared to using vibration analysis alone. By combining the strengths of both methods, the system achieved a 98% prediction accuracy, allowing the factory to schedule maintenance activities more effectively and reduce downtime by 35%.

These findings illustrate the diverse range of PdM techniques applied across different industrial settings, showcasing the potential benefits of integrating real-time data collection, machine learning algorithms, and IoT systems. The consistent results across these studies highlight the ability of PdM to significantly reduce downtime, extend the lifespan of machinery, and improve operational efficiency. The application of deep learning algorithms, in particular, has shown exceptional promise in improving prediction accuracy, particularly in complex systems with large volumes of sensor data.

However, despite these successes, the research also highlights several challenges that remain in the widespread implementation of PdM systems. One such challenge is the high initial cost associated with installing IoT sensors and developing machine learning models, which can be a barrier for small and medium-sized enterprises (SMEs). While the long-term savings from reduced downtime and maintenance costs often justify the initial investment, the upfront cost remains a significant obstacle for many manufacturers. Additionally, the complexity of machine learning models and the need for skilled personnel to operate and maintain these systems complicate the adoption of PdM, particularly in industries with limited resources for training and technology deployment.

The integration of PdM with existing manufacturing systems also poses challenges, particularly in industries with older machinery or legacy systems that may not be compatible with modern sensor technologies. Upgrading these systems requires careful planning and additional investments in infrastructure, which can further delay the implementation of PdM.

Furthermore, the reliability of predictive maintenance systems depends heavily on the quality and consistency of the data collected from sensors. Issues such as sensor malfunction, data noise, and gaps in data collection can affect the accuracy of failure predictions, leading to false positives or missed failures. Future research should focus on developing methods to ensure the quality and consistency of sensor data, particularly in industrial environments where equipment and conditions can vary significantly.

Discussion

The findings from the studies presented in the results section demonstrate the transformative potential of predictive maintenance (PdM) in enhancing machine tool reliability. The integration of advanced technologies, such as Internet of Things (IoT) sensors, machine learning (ML), and deep learning (DL), has significantly improved predictive capabilities, offering substantial benefits in terms of reduced downtime, extended machine lifespan, and lowered maintenance costs. These advancements underscore the growing importance of data-driven strategies in manufacturing, marking a departure from traditional reactive maintenance practices to proactive, predictive approaches.

The application of machine learning, particularly support vector machines (SVM), decision trees, and deep learning algorithms like Convolutional Neural Networks (CNNs), has proven to be pivotal in enhancing the accuracy of PdM systems. Singh *et al*. (2022) [13] demonstrated that machine learning models, combined with real-time data collection from vibration sensors, were able to predict failures with 92% accuracy, reducing unplanned downtime by 40%. Similarly, Hirsch (2024) [5] showcased that deep learning models, particularly CNNs, provided a significant leap in prediction accuracy, achieving 99.1% accuracy in predicting tool wear. These results align with the broader literature that highlights the superiority of deep learning algorithms over traditional methods in terms of prediction accuracy. For instance, Li *et al*. (2020) [10] found that CNNs performed exceptionally well in processing multi-dimensional sensor data, reaching a 97% prediction accuracy for failure detection. The ability of these advanced models to analyze complex, high-dimensional datasets allows for more precise predictions, which is critical for reducing the risk of unexpected breakdowns and improving overall equipment effectiveness (OEE).

Incorporating IoT technologies into PdM systems has further enhanced predictive maintenance strategies by enabling real-time, continuous monitoring of machine tools. Liu *et al*. (2021) [9] demonstrated the effectiveness of IoT-enabled PdM systems in an automotive manufacturing plant, where sensor data was collected and analyzed to predict tool failure, leading to a 30% reduction in maintenance costs and a 20% increase in production uptime. This result highlights the role of IoT in providing comprehensive insights into the health of machinery, facilitating timely maintenance interventions. By continuously monitoring machine conditions, IoT-enabled PdM systems provide a more proactive approach to maintenance, allowing manufacturers to move from scheduled or reactive maintenance to condition-based maintenance, which can greatly improve operational efficiency.

The use of hybrid models combining multiple PdM techniques has also shown significant promise. Zhao *et al*. (2020) [8] proposed a hybrid PdM model that integrated vibration analysis with machine learning algorithms, achieving a failure prediction accuracy of 98%. The study showed that combining traditional diagnostic methods with advanced machine learning models provided more reliable predictions than either method alone. This supports findings from previous studies, such as those by Yang *et al*. (2021) [14], who found that integrating cloud-based systems with IoT sensors improved production efficiency by 15% and reduced machine downtime by 20%. The success of hybrid PdM approaches suggests that a multi-faceted strategy that combines different techniques can provide more robust and accurate predictions, especially in complex industrial environments.

However, while the results demonstrate the substantial benefits of PdM, several challenges and limitations persist. One of the most significant barriers is the initial cost of implementing PdM systems, particularly for small and medium-sized enterprises (SMEs). The setup of IoT infrastructure, including sensors, cloud computing platforms, and machine learning models, requires a considerable investment in both hardware and software. Singh *et al*. (2022) [13] noted that the high upfront costs associated with PdM implementation could be a deterrent for many manufacturers, particularly those with limited budgets. This challenge is corroborated by the findings of Lee & Kim (2020) [8], who reported that despite the long-term benefits, the initial investment in PdM technology remains a major barrier to its adoption, particularly in industries with smaller profit margins. Overcoming this financial barrier may require the development of more affordable PdM solutions that are scalable and adaptable to different industrial contexts.

Another challenge highlighted in the literature is the complexity of integrating PdM systems into existing manufacturing infrastructures. Many industries still rely on legacy equipment and older maintenance systems, which may not be compatible with modern IoT and machine learning technologies. As noted by IoT Analytics (2023) [4], the integration of PdM systems with legacy machinery remains a significant obstacle, requiring significant upgrades to existing systems and processes. Manufacturers must carefully plan the transition to PdM, ensuring that new technologies are compatible with their current operations. This requires not only financial investment but also expertise in system integration and data management.

The quality of data collected by sensors also plays a critical role in the success of PdM systems. Poor-quality or inconsistent data can lead to inaccurate predictions, resulting in false alarms or missed failures. Kusiak *et al*. (2017) [11] highlighted the importance of ensuring data quality in PdM applications, noting that unreliable data can undermine the effectiveness of predictive models. Future research should focus on improving data collection methods, ensuring that sensors provide accurate and consistent measurements. Additionally, the development of advanced data preprocessing techniques to filter out noise and handle missing data will be essential for enhancing the reliability of PdM systems.

Moreover, while PdM systems provide significant predictive capabilities, they are not infallible. As pointed out by Cummins (2024) [7], the interpretability of machine learning models is often a concern in industrial applications. Many PdM systems operate as “black boxes,” making it difficult for operators to understand the rationale behind predictions and maintenance recommendations. This lack of transparency can hinder the widespread adoption of PdM systems, as maintenance personnel may be hesitant to trust models they do not fully understand. To address this issue, the future of PdM systems may lie in the integration of explainable AI (XAI) techniques, which provide more transparent and interpretable models that users can trust. Research into XAI for PdM could lead to more user-friendly systems that are easier to implement and adopt.

Finally, the human factors involved in the adoption of PdM systems cannot be overlooked. As highlighted by Zhu *et al*. (2021) [12], organizational resistance to change remains a significant barrier to the widespread implementation of PdM technologies. Manufacturing companies accustomed to traditional maintenance practices may be reluctant to invest in new technologies and alter established workflows. Successful PdM adoption requires a cultural shift within organizations, where maintenance teams, machine operators, and data scientists collaborate to ensure the system is used effectively and continuously optimized. Training programs and clear communication about the benefits of PdM will be crucial in overcoming this resistance.

Conclusion

This research has explored the significant advancements in predictive maintenance (PdM) techniques aimed at enhancing machine tool reliability. Through the integration of machine learning, Internet of Things (IoT) technologies, and advanced analytics, PdM systems have demonstrated considerable potential in reducing unplanned downtime, extending the lifespan of machine tools, and improving overall operational efficiency. The findings from recent studies have shown that predictive maintenance can predict tool failures with remarkable accuracy, enabling manufacturers to transition from reactive maintenance practices to more proactive, data-driven strategies.

The application of machine learning algorithms, particularly deep learning models like Convolutional Neural Networks (CNNs), has proven to be a game-changer, achieving high levels of prediction accuracy in complex industrial environments. Similarly, IoT-based PdM systems, which allow for continuous monitoring and real-time data collection, have further enhanced the ability to detect anomalies and predict failures before they disrupt production. These advancements have been shown to significantly reduce maintenance costs and improve overall equipment effectiveness (OEE) across various industries, particularly in automotive, aerospace, and semiconductor manufacturing.

However, several challenges remain that hinder the widespread adoption of PdM systems. High initial costs, integration complexities, and the need for skilled personnel continue to be significant barriers, particularly for small and medium-sized enterprises (SMEs). Moreover, issues related to data quality, system compatibility with legacy equipment, and the interpretability of machine learning models pose obstacles to fully realizing the potential of PdM. These challenges underscore the need for continued research to develop cost-effective solutions and to address the technical and organizational barriers to PdM implementation.

Future research should focus on several key areas. First, developing more affordable and scalable PdM solutions that can be easily integrated into existing manufacturing systems will be crucial in making these technologies accessible to a broader range of industries. Research into improving the quality and consistency of sensor data, as well as advanced data preprocessing techniques, will enhance the reliability and accuracy of PdM systems. Additionally, further investigation into Explainable AI (XAI) methods will be essential for increasing the transparency and trustworthiness of predictive models, allowing operators to better understand and act upon maintenance predictions.

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