

# Machine Learning Approach based Predictive Maintenance in Industrial Equipment

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## ABSTRACT

*Predictive Maintenance has emerged as a critical strategy for optimizing the reliability and performance of industrial equipment. Traditional preventive maintenance approaches are often costly and inefficient, leading to unnecessary downtime and maintenance expenses. Machine learning, a branch of Artificial Intelligence, has proven to be a powerful tool for predictive maintenance. This research paper explores the Machine Learning techniques application in predictive maintenance for industrial equipment, highlighting its benefits, challenges, and real-world implementations.*

**Key Words:** Predictive Maintenance, Machine Learning, Industrial Equipment, Data-Driven Maintenance, Sensor Data.

## 1. INTRODUCTION

### 1.1 Overview

This research provides an all-inclusive summary of machine learning based predictive maintenance in industrial contexts, addressing three core objectives. Firstly, it delves into the critical process of feature engineering, highlighting its central role in improving the accuracy of predictive maintenance models [1]. Feature engineering involves selecting and crafting data features that significantly impact the efficacy of machine learning algorithms in forecasting equipment failures. Secondly, this study thoroughly examines the challenges and intricacies of implementing machine learning-driven predictive maintenance in real-world industrial settings. It identifies obstacles ranging from data quality issues to deployment complexities and offers practical solutions to overcome these hurdles [2]. These insights ensure the successful adoption of predictive maintenance strategies in industrial environments.

Lastly, the research extends beyond academic exploration to provide valuable insights and actionable recommendations. These findings cater to a diverse audience, including industrial professionals aiming to optimize equipment reliability, researchers exploring advanced predictive maintenance

techniques, and policymakers considering data-driven strategies for industrial enhancement [4].

### 1.2 Motivation

The motivation for this research stems from the pressing need to enhance the reliability, efficiency, and cost-effectiveness of industrial equipment maintenance practices. Traditional maintenance approaches often lead to costly and unplanned downtime, which can significantly impact industrial operations and profitability. By harnessing the power of Machine Learning and predictive maintenance, this work aims to proactively identify potential equipment failures, allowing for timely interventions and resource allocation. Ultimately, this research seeks to reduce maintenance costs, optimize asset reliability, and revolutionize the way industrial equipment is managed, ensuring a more sustainable and competitive future for industrial enterprises.

### 1.3 Objective

The objective of the research is given below:

- To examine the process of feature engineering and its role in improving the accuracy of predictive maintenance models.
- To identify and confer the challenges and potential solutions in implementing Machine Learning based predictive maintenance in real-world industrial environments.
- To provide valuable insights and recommendations for industrial professionals, researchers, and policymakers looking to adopt Machine Learning-based predictive maintenance strategies in their organizations.

## 2. Literature Review

### 2.1 Background

Over the years, industries have faced challenges related to unplanned downtime, escalating maintenance costs, and



suboptimal asset utilization [5]. Traditional maintenance approaches based on fixed schedules or reactive responses have proven to be inadequate and costly. To address these issues, the concept of predictive maintenance has gained prominence [6]. Numerous studies in the literature have explored the potential of predictive maintenance, highlighting its ability to proactively predict equipment failures by analyzing data generated by sensors, historical maintenance records, and environmental factors. Machine Learning, a branch of artificial intelligence, has emerged as a critical means in this endeavor due to its capacity to process vast datasets and detect complex patterns [7].

The literature has extensively covered various aspects of predictive maintenance, including data collection, preprocessing, feature engineering, and the application of diverse Machine Learning algorithms such as regression, classification, and time-series forecasting. Case studies and real-world implementations in different industrial domains have showcased significant cost savings, reduced downtime, and enhanced asset reliability achieved through Machine Learning-based predictive maintenance [8]. Furthermore, the literature highlights the evolving landscape of predictive maintenance, including the integration of IoT devices and deep learning techniques, indicating the ongoing transformation of maintenance practices in response to technological advancements. This literature review background highlights the need for further research and development in this area to harness the full potential of Machine Learning for predictive maintenance in industrial equipment [9].

## 2.2 Predictive Maintenance

Predictive Maintenance is a proactive maintenance approach that employs data-driven techniques to anticipate equipment failures before they occur. It stands in contrast to traditional, reactive maintenance practices, which involve fixing machinery only after it breaks down, often leading to costly downtime and repairs. In predictive maintenance, various data sources are harnessed, such as sensor data, past maintenance records, and environmental factors. Machine Learning and statistical analysis are then applied to these data sets to detect patterns, anomalies, and trends. By continuously monitoring equipment conditions, predictive maintenance models can forecast when a machine is likely to malfunction, allowing for timely preventive actions, such as servicing or component replacement [10].

The benefits of predictive maintenance are substantial, including reduced downtime, minimized maintenance costs, improved equipment reliability, and optimized asset utilization. Industries ranging from manufacturing and transportation to energy and healthcare have adopted predictive maintenance to enhance operational efficiency and competitiveness [11]. This approach maximizes the lifespan of critical machinery, minimizes unplanned downtime, and

ultimately increases productivity and profitability. As technology continues to advance, predictive maintenance is poised to perform an increasingly vital role in modern industrial operations, paving the way for smarter and more efficient maintenance practices [3].

## 2.3 Industrial Equipment

Industrial equipment refers to a broad category of machinery, devices, and tools specifically designed for use in industrial settings to facilitate various manufacturing, processing, and production activities. These equipment types are fundamental to virtually all industrial sectors, including manufacturing, construction, energy generation, and transportation [12]. Industrial equipment encompasses a wide range of items, from heavy machinery such as turbines, boilers, and large-scale assembly lines, to smaller tools and instruments like lathes, CNC machines, and sensors. It plays a pivotal role in streamlining and automating industrial processes, enhancing productivity, precision, and efficiency. These equipment pieces are typically designed to withstand demanding and continuous operation, often in harsh environments. They are crucial for tasks such as cutting, shaping, welding, measuring, packaging, and transporting materials or products within an industrial facility [13].

With advancements in technology, industrial equipment is becoming more interconnected and sophisticated. The integration of sensors, data analytics, and automation technologies is transforming traditional industrial equipment into smart, interconnected systems, enabling real-time monitoring, predictive maintenance, and improved decision-making [14].

The efficient and reliable operation of industrial equipment is essential for achieving high-quality production, meeting production deadlines, and ensuring the safety of workers. Maintenance and upkeep of this equipment are critical to prevent downtime and maintain optimal performance, making predictive maintenance techniques increasingly valuable in industrial settings [15].

## 2.4 Machine Learning Technique for Industrial Application

Machine Learning techniques have gained significant grip in industrial applications due to their ability to process huge amounts of data and make data-driven decisions, which can enhance efficiency, productivity, and safety in various industrial processes. These techniques are versatile and adaptable to a wide range of industrial domains, making them invaluable tools for optimizing operations [7].

In industrial applications, Machine Learning is employed for tasks such as predictive maintenance, quality control, process optimization, and anomaly detection. Predictive maintenance, for instance, leverages algorithms to analyze sensor data and historical maintenance records to predict when machinery is



likely to fail. This proactive approach minimizes unplanned interruption and decreases maintenance costs.

Quality control benefits from Machine Learning's ability to detect defects in real-time, safeguarding that only high-quality products reach the market. Process optimization relies on Machine Learning to analyze complex processes and identify opportunities for improvement, resulting in increased efficiency and reduced waste [12].

Furthermore, Machine Learning techniques excel in anomaly detection, where they can identify unusual patterns or deviations from normal operation, potentially indicating faults or security breaches [17]. These applications showcase how Machine Learning can transform industrial operations, making them more efficient, reliable, and cost-effective [16].

As industries continue to generate large volumes of data, the adoption of Machine Learning techniques in industrial settings is expected to grow, enabling further advancements in automation and data-driven decision-making for enhanced productivity and competitiveness.

## 2.5 Related Work

Numerous studies have explored the application of Machine Learning techniques in various industrial domains, yielding valuable insights and practical solutions [2]. One notable area of research focuses on data-driven approaches for predictive maintenance. These studies emphasize the importance of data collection and preprocessing, highlighting the need for high-quality data to train accurate Machine Learning models. Researchers have developed methodologies for integrating data from sensors, historical maintenance records, and other sources to predict equipment failures with greater precision [3]. Additionally, Machine Learning algorithms have been extensively investigated for their suitability in predictive maintenance tasks. Regression models, classification algorithms, and time-series forecasting methods have been applied to different types of industrial equipment to predict when maintenance is needed. Researchers have also explored the benefits of ensemble methods and deep learning techniques to improve prediction accuracy [7].

Real-world implementations and case studies have confirmed the practicality and cost-effectiveness of Machine Learning-based predictive maintenance. Industries such as manufacturing, energy, and aviation have reported substantial reductions in maintenance costs and downtime, leading to improved operational competence and competitiveness [5]. Furthermore, emerging trends in the field include the integration of Internet of Things (IoT) devices for real-time data acquisition, edge computing for faster decision-making, and the use of explainable Artificial Intelligent (AI) techniques to enhance model interpretability. These developments indicate a promising future for Machine Learning-based predictive maintenance in industrial

equipment, with ongoing research aimed at addressing challenges and optimizing its application across various sectors [3].

## 2.6 Summary

Machine Learning-based predictive maintenance in industrial equipment is a growing field with significant benefits. Research highlights the importance of high-quality data, data preprocessing, and various Machine Learning algorithms for accurate predictions. Real-world implementations have shown reduced maintenance costs and minimized downtime in industries like manufacturing and energy. Emerging trends include Internet of Things (IoT) integration, edge computing, and explainable AI. This research aims to revolutionize maintenance practices, ensuring cost-effectiveness, and enhancing asset reliability across various industrial sectors.

# 3. Machine Learning Technique used in Industrial Equipment and Maintenance

## 3.1 Methodology

The methodology for conducting research on Machine Learning-based predictive maintenance in industrial equipment involves an orderly approach to data collection, analysis, and model development. The following outline is the key components of the methodology shown in figure.

**Data Collection:** Gather relevant data sources, including sensor data from industrial equipment, historical maintenance records, environmental factors, and any other pertinent information. Ensure data quality and completeness.

**Data Preprocessing:** Clean, preprocess, and convert the data to make it suitable for Machine Learning analysis. This includes handling missing values, outlier detection, and feature scaling. **Feature Engineering:** Identify and create relevant features that can enhance the predictive capabilities of the model. Feature selection techniques may be employed to determine the most significant attributes.

**Selection of Machine Learning Algorithms:** Choose appropriate Machine Learning algorithms based on the specific predictive maintenance task. Regression, classification, time-series forecasting, and anomaly detection algorithms are common choices.

**Model Training:** Split the data into training and validation sets and use the training data to train the Machine Learning model. Tune hyperparameters for optimum performance.

**Model Evaluation:** Evaluate the model's performance using suitable metrics such as accuracy, precision, recall, F1-score, or mean absolute error, depending on the problem type.

**Deployment:** If applicable, deploy the trained model in a real-time or near-real-time environment to make predictions and trigger maintenance actions.

**Monitoring and Maintenance:** Non-stop monitor the model's performance and retrain it as needed to adapt to changing conditions and data patterns.

**Documentation:** Document the entire process, including data sources, preprocessing steps, model architecture, hyperparameters, and evaluation results.

**Reporting and Interpretation:** Present the findings, insights, and predictions generated by the model in a clear and understandable manner, allowing stakeholders to make informed decisions.

**Validation and Testing:** Validate the model's predictions through testing in a controlled environment or with real-world data to ensure its reliability and effectiveness.

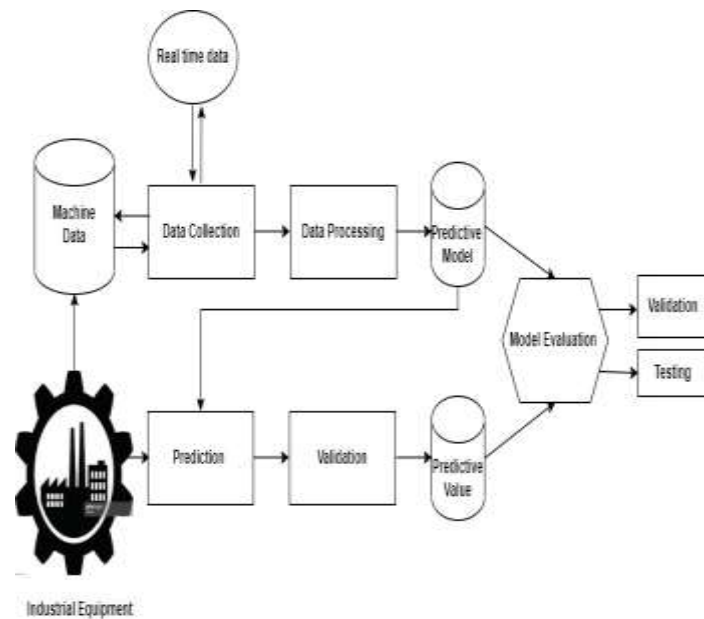


Figure 1.1: Methodology

### 3.2 Recent Research Work

The recent research works in predictive maintenance of industrial equipment using Machine Learning are as follows

**Deep Learning for Predictive Maintenance:** Deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have grown acceptance for predictive maintenance tasks. Researchers have discovered the use of deep learning models to analyze sensor data and time-series data from industrial equipment for more accurate fault detection and remaining useful life prediction.

**Edge Computing and IoT Integration:** The integration of Internet of Things (IoT) devices and edge computing has become more prevalent. This allows for real-time data collection and analysis at the equipment level, enabling faster decision-making and reducing the need for transmitting large volumes of data to central servers.

**Explainable AI (XAI):** Researchers have focused on improving the interpretability of Machine Learning models in

predictive maintenance. Explainable AI techniques aim to make the decision-making process of models more transparent and understandable, which is crucial for gaining trust in safety-critical industrial applications.

**Transfer Learning:** Transfer learning, a technique where models are pre-trained on bulky datasets and then fine-tuned for specific tasks, has been applied to predictive maintenance. This approach can be particularly useful when dealing with limited labeled data for rare failure events.

**Real-world Implementations:** Many industries, including manufacturing, aviation, and energy, have reported successful implementations of predictive maintenance systems. These real-world case studies often highlight significant cost savings, reduced downtime, and improved equipment reliability.

**Prognostics and Health Management (PHM):** PHM has gained attention as a comprehensive approach that combines data-driven predictive maintenance with system health monitoring. PHM systems aim to provide a holistic view of equipment health, taking into account both current condition monitoring and future failure predictions.

**AI Platforms and Tools:** The availability of AI platforms and tools designed specifically for industrial predictive maintenance has grown. These platforms often provide end-to-end solutions, from data collection and preprocessing to model development and deployment.

**Interdisciplinary Research:** Researchers from diverse fields, including Machine Learning, engineering, and domain-specific industries, are collaborating to develop more effective predictive maintenance solutions. This interdisciplinary approach ensures that models are better aligned with the operational requirements and constraints of specific industrial domains.

**AI Ethics and Bias Mitigation:** As with AI in other applications, the field of predictive maintenance is increasingly focused on addressing ethical considerations and biases in Machine Learning models to ensure fairness, transparency, and responsible use.

Keep in mind that the field of predictive maintenance is continually evolving, and new research, techniques, and case studies are emerging regularly. For the most up-to-date information, it's essential to consult recent research papers, industry publications, and conferences in the field.

## 4. Application Area and Future Scope

Machine Learning-based predictive maintenance is widely applied in manufacturing, energy, and aviation to prevent equipment failures and reduce downtime. The future of predictive maintenance includes enhanced AI algorithms, IoT integration, and a focus on sustainability, making it applicable

across diverse industries, with broader adoption and continuous innovation.

#### 4.1 Application

Machine Learning-based predictive maintenance in industrial equipment has found numerous applications across various industries [18]. Here are some notable applications:

1. **Manufacturing:** Predictive maintenance is widely used in manufacturing industries to prevent costly production disruptions. Machines such as CNC machining centers, robotics, and conveyor systems are continuously monitored for anomalies, enabling timely maintenance and reducing downtime.
2. **Energy and Utilities:** Power plants, wind turbines, and oil rigs use predictive maintenance to ensure uninterrupted energy production. By monitoring equipment health and predicting failures, energy companies can optimize maintenance schedules and minimize service costs.
3. **Aviation:** Airlines use predictive maintenance for aircraft components like engines, landing gear, and avionics. This ensures the safety and reliability of flights while reducing unplanned maintenance events.
4. **Transportation:** In the transportation sector, predictive maintenance is applied to vehicles, railway systems, and infrastructure. It helps prevent accidents, optimize maintenance schedules, and enhance passenger safety.
5. **Healthcare:** Medical equipment, such as MRI machines and X-ray equipment, benefit from predictive maintenance to ensure their continuous operation. Unplanned downtime can disrupt patient care, making predictive maintenance crucial in healthcare settings.
6. **Oil and Gas:** In this sector, pipelines, drilling equipment, and offshore platforms are subject to harsh conditions. Predictive maintenance helps prevent costly equipment failures and environmental disasters.
7. **Mining:** Heavy machinery used in mining operations, such as excavators and haul trucks, undergo predictive maintenance to reduce downtime, extend equipment life, and improve worker safety.
8. **Agriculture:** Farm equipment, including tractors and harvesters, relies on predictive maintenance to maximize efficiency during critical planting and harvesting seasons.
9. **Telecommunications:** Telecom companies use predictive maintenance for maintaining network infrastructure, ensuring uninterrupted connectivity for customers.
10. **Construction:** Construction equipment, such as cranes and bulldozers, is subject to heavy wear and tear. Predictive maintenance helps construction

companies plan maintenance activities efficiently, reducing project delays.

11. **Railways:** Rail companies use predictive maintenance for trains and track infrastructure. This enhances passenger safety, reduces service disruptions, and lowers maintenance costs.
12. **Maritime:** Ships and maritime equipment are maintained predictively to prevent breakdowns during voyages, ensuring maritime safety and smooth operations.
13. **Chemical and Process Industries:** Predictive maintenance is applied to critical equipment in chemical plants and refineries, where equipment failures can lead to hazardous situations.
14. **Food Processing:** Equipment in food processing plants, like ovens and conveyor belts, undergo predictive maintenance to maintain food safety standards and prevent contamination.
15. **Renewable Energy:** Wind turbines and solar farms benefit from predictive maintenance to optimize energy generation and reduce downtime.

#### 4.2 Advantages

Following are the advantages of Predictive Maintenance in Industrial Equipment using Machine Learning Approach [19].

1. **Reduced Downtime:** By predicting equipment fiascos before they occur, predictive maintenance minimizes inadvertent downtime. This ensures continuous operations, higher productivity, and reduced production losses.
2. **Cost Savings:** Predictive maintenance optimizes maintenance schedules, reducing the need for unnecessary maintenance tasks. This leads to cost savings in terms of labor, spare parts, and equipment replacement.
3. **Extended Equipment Lifespan:** Timely maintenance and repairs based on predictive insights help prolong the life of industrial equipment, reducing the frequency of replacements and associated costs.
4. **Improved Safety:** Predictive maintenance reduces the risk of sudden equipment failures, which can lead to accidents or injuries. Enhanced safety is particularly crucial in industries with safety-critical equipment.
5. **Optimized Resource Allocation:** Maintenance resources, including labor and spare parts, can be allocated more efficiently based on the specific needs identified by predictive models.
6. **Better Inventory Management:** Predictive maintenance reduces the need for maintaining excessive spare parts inventory, saving storage space and costs.

7. **Data-Driven Decision-Making:** It allows for data-driven decision-making by providing actionable insights into equipment health and performance trends.
8. **Enhanced Operational Efficiency:** Predictive maintenance contributes to smoother and more efficient industrial processes, minimizing disruptions and improving overall operational efficiency.
9. **Improved Equipment Reliability:** By addressing issues before they lead to failures, predictive maintenance increases the reliability of industrial equipment, reducing the likelihood of breakdowns.
10. **Environmental Benefits:** Reduced equipment downtime and optimized maintenance contribute to energy savings and reduced emissions, making predictive maintenance environmentally friendly.
11. **Customer Satisfaction:** Industries with high uptime requirements, such as utilities or transportation, can meet customer expectations more consistently through predictive maintenance.
12. **Competitive Advantage:** Companies implementing predictive maintenance gain a competitive edge by delivering more reliable products and services while reducing operational costs.
13. **Proactive Maintenance Culture:** Predictive maintenance encourages a proactive maintenance culture, where equipment issues are addressed before they become critical, fostering a culture of continuous improvement.

#### 4.3 Disadvantages

The disadvantages of Predictive Maintenance in Industrial Equipment using Machine Learning Approach are as follows

1. **Data Quality and Availability:** Predictive maintenance heavily relies on high-quality and comprehensive data. In some cases, acquiring and maintaining such data can be challenging, especially for older equipment that lacks built-in sensors. Incomplete or unreliable data can lead to inaccurate predictions.
2. **Complex Implementation:** Implementing predictive maintenance systems can be complex and resource-intensive. It requires the integration of sensors, data collection infrastructure, and the development of Machine Learning models. Small and medium-sized enterprises (SMEs) may face difficulties in adopting these systems due to cost and expertise constraints.
3. **Model Interpretability:** Some advanced Machine Learning models used in predictive maintenance, such as deep neural networks, are often considered "black boxes." Understanding the reasoning behind model predictions can be difficult, which may raise concerns in safety-critical applications where interpretability is crucial.

4. **Maintenance Cost:** While predictive maintenance can reduce overall maintenance costs, implementing and maintaining the predictive maintenance system itself incurs costs. This includes the expenses associated with sensors, data storage, model development, and ongoing monitoring and maintenance. These costs can be substantial, especially for smaller organizations.

#### 4.4 Future Scope

The future scope related to Predictive Maintenance in industrial equipment using Machine Learning approach is as follows

1. **Advanced Machine Learning Algorithms:** Ongoing research is likely to lead to the development of more advanced Machine Learning algorithms specifically tailored for predictive maintenance. These algorithms will improve prediction accuracy and reduce false alarms, making maintenance practices even more efficient.
2. **Explainable AI (XAI):** As Machine Learning models become more complex, there is a growing need for XAI techniques that provide transparency and interpretability. Future research will focus on making predictive maintenance models more understandable, enabling better decision-making and trust in AI-driven maintenance recommendations.
3. **Edge Computing and IoT Integration:** The integration of IoT devices and edge computing will continue to expand. This will enable real-time data processing and decision-making at the equipment level, reducing latency and further enhancing the timeliness of maintenance actions.
4. **Predictive Analytics Ecosystems:** The development of comprehensive predictive analytics ecosystems will become more prevalent. These ecosystems will offer end-to-end solutions, including data acquisition, preprocessing, modeling, deployment, and monitoring, simplifying the implementation of predictive maintenance systems.
5. **Autonomous Maintenance Systems:** Research and development efforts will aim to create more autonomous maintenance systems that can not only predict equipment failures but also initiate maintenance actions without human intervention when necessary. This will reduce response times and enhance efficiency.
6. **Integration with Augmented Reality (AR) and Virtual Reality (VR):** AR and VR technologies can enhance the training and support of maintenance personnel. Integration with predictive maintenance systems will provide technicians with real-time data overlays, visualizations, and guidance for maintenance tasks.



7. **AI Ethics and Bias Mitigation:** As AI applications grow, there will be an increased focus on addressing ethical considerations and mitigating biases in predictive maintenance models. Ensuring fairness, transparency, and responsible use of AI will be essential.
8. **Cross-Industry Collaboration:** Collaborative efforts across industries will lead to the development of standardized approaches and best practices for predictive maintenance. Shared knowledge and experiences will accelerate the adoption of these practices.
9. **Customized Solutions:** Predictive maintenance models will become more custom-made to the definite needs and challenges of different industries and equipment types. Customized solutions will optimize maintenance strategies based on domain-specific requirements.
10. **Predictive Maintenance as a Service (PMaaS):** The concept of PMaaS will gain traction, allowing organizations to access predictive maintenance capabilities through cloud-based services. This will reduce the barriers to entry and make predictive maintenance more accessible to a wider range of businesses.

## 5. Conclusion

In conclusion, this research has addressed its objectives by delving into the critical aspects of machine learning-based predictive maintenance in industrial settings. This work scrutinized the process of feature engineering, recognizing its pivotal role in enhancing the precision of predictive maintenance models. Additionally, this work meticulously examined the challenges associated with the practical implementation of machine learning-based predictive maintenance in real-world industrial environments, while also offering viable solutions to overcome these hurdles. Our findings not only contribute to the academic discourse but also provide practical insights and recommendations for industrial professionals, researchers, and policymakers who are considering the adoption of Machine Learning-based predictive maintenance strategies. As industries increasingly harness the power of data-driven approaches, this work serves as a guidepost for optimizing equipment reliability, minimizing downtime, and ultimately advancing operational efficiency in industrial domains.

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