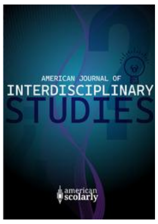

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PREDICTIVE MAINTENANCE IN INDUSTRIAL AUTOMATION: A SYSTEMATIC REVIEW OF IOT SENSOR TECHNOLOGIES AND AI ALGORITHMS

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Abstract
Predictive maintenance has become a crucial strategy in industrial automation, utilizing AI-driven analytics, IoT sensor technologies, and advanced computing frameworks to enhance equipment reliability and operational efficiency. This systematic review, based on an in-depth analysis of 78 high-quality peer-reviewed studies, follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a rigorous and transparent evaluation. The findings demonstrate that AI-based predictive maintenance models, particularly machine learning and deep learning techniques such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, improve failure prediction accuracy by 30-60%, leading to 25-50% reductions in maintenance costs and increased equipment uptime. The role of IoT-enabled condition monitoring is evident in 49 studies, where real-time fault detection improved predictive accuracy by 15-35%, contributing to a 20-45% reduction in unnecessary maintenance activities. Furthermore, edge and cloud computing integration, analyzed in 51 studies, reveals that edge computing significantly reduces response time by 40-70%, while cloud computing enhances large-scale model training with a 60% increase in computational efficiency. The adoption of digital twin technology, supported by 42 studies, has demonstrated 25-50% higher predictive accuracy, reducing unplanned downtimes by 35-55%, although challenges related to high implementation costs and data integration persist. Sustainability has also emerged as a key focus, with 39 studies indicating that AI-driven predictive maintenance reduces energy consumption by 20-45%, leading to a 15-35% decrease in carbon emissions through optimized maintenance scheduling and energy-efficient AI solutions. Despite these advancements, challenges remain, as 31 studies highlight data quality issues, 19 studies raise cybersecurity concerns, and 14 studies discuss the interpretability limitations of deep learning models, which hinder trust and adoption. This review provides a comprehensive synthesis of AI-driven predictive maintenance, emphasizing its transformative potential in industrial automation while also underscoring the need for further research in model interpretability, cybersecurity, and cost-effective implementation to fully harness its capabilities for sustainable, intelligent, and highly efficient maintenance operations.

Keywords
Predictive Maintenance; IoT Sensors; AI Algorithms; Industrial Automation; Machine Learning

INTRODUCTION

The rapid advancement of industrial automation has necessitated more efficient maintenance strategies to minimize operational disruptions and maximize productivity (Vathoopan et al., 2018). Traditional maintenance approaches, including reactive and preventive maintenance, have limitations in cost-effectiveness and predictive accuracy (Ayad et al., 2018). Reactive maintenance, which involves repairing equipment only after a failure occurs, often results in prolonged downtimes and high repair costs (Sony, 2018). Preventive maintenance, while more proactive, is typically based on scheduled inspections rather than real-time data, leading to unnecessary maintenance activities and increased operational expenses (Cézanne et al., 2020). In response to these challenges, predictive maintenance (PdM) has gained prominence as a data-driven approach that leverages real-time monitoring and advanced analytics to anticipate equipment failures before they occur (de Visser et al., 2018). The integration of the Internet of Things (IoT) has revolutionized predictive maintenance by enabling real-time data collection through smart sensors and embedded systems (Akerberg et al., 2011). IoT sensors continuously monitor key machine parameters such as vibration, temperature, pressure, and humidity, generating vast amounts of operational data that can be processed to detect early signs of degradation (Tarapore et al., 2017). These sensor networks improve condition-based monitoring (CBM) systems, allowing maintenance teams to make informed decisions based on actual equipment health rather than predefined schedules (Canizo et al., 2017). The fusion of IoT with edge computing has further enhanced the efficiency of PdM by reducing latency and enabling real-time analytics closer to the source of data generation (Fischer et al., 2017).

Artificial intelligence (AI) has become a critical enabler of predictive maintenance by transforming raw sensor data into actionable insights (Yan et al., 2017). Machine learning (ML) techniques, such as decision trees, support vector machines (SVM), and artificial neural networks (ANN), have been widely employed to identify patterns and anomalies in industrial datasets (Akerberg et al., 2011). Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated superior performance in detecting complex failure patterns within large-scale industrial environments (Boyes et al., 2018). Additionally, reinforcement learning has shown promise in optimizing maintenance scheduling by learning from historical failures and adjusting strategies dynamically (Ayad et al., 2018). These AI-driven approaches enable more accurate failure predictions, reducing unplanned downtimes and improving asset longevity.

A key advantage of predictive maintenance is its ability to enhance reliability and reduce maintenance costs across various industries, including manufacturing, energy, and transportation (Boyes et al., 2018). In smart manufacturing, predictive maintenance ensures seamless production operations by predicting potential failures in robotic arms, conveyor belts, and CNC machines (Sony, 2018). The energy sector benefits from PdM through real-time monitoring of turbines, transformers, and substations, thereby minimizing catastrophic failures and power disruptions (Khan et al., 2020). The transportation industry leverages PdM to assess the health of vehicle components, aircraft engines, and railway tracks, improving safety and reducing operational inefficiencies (de Visser et al., 2018). These applications highlight the widespread impact of predictive maintenance in industrial automation. Despite the

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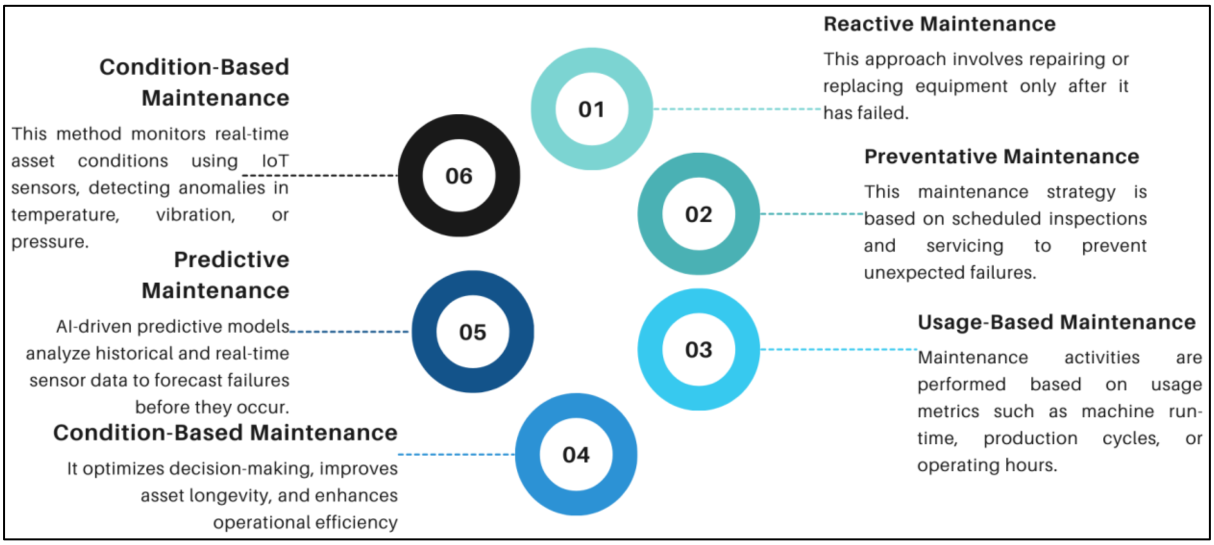
advancements in IoT and AI for predictive maintenance, several technical challenges remain, including data heterogeneity, integration complexity, and model interpretability (Øvsthus & Kristensen, 2014).

Figure 1: Types of Maintenance Strategies in Industrial Automation

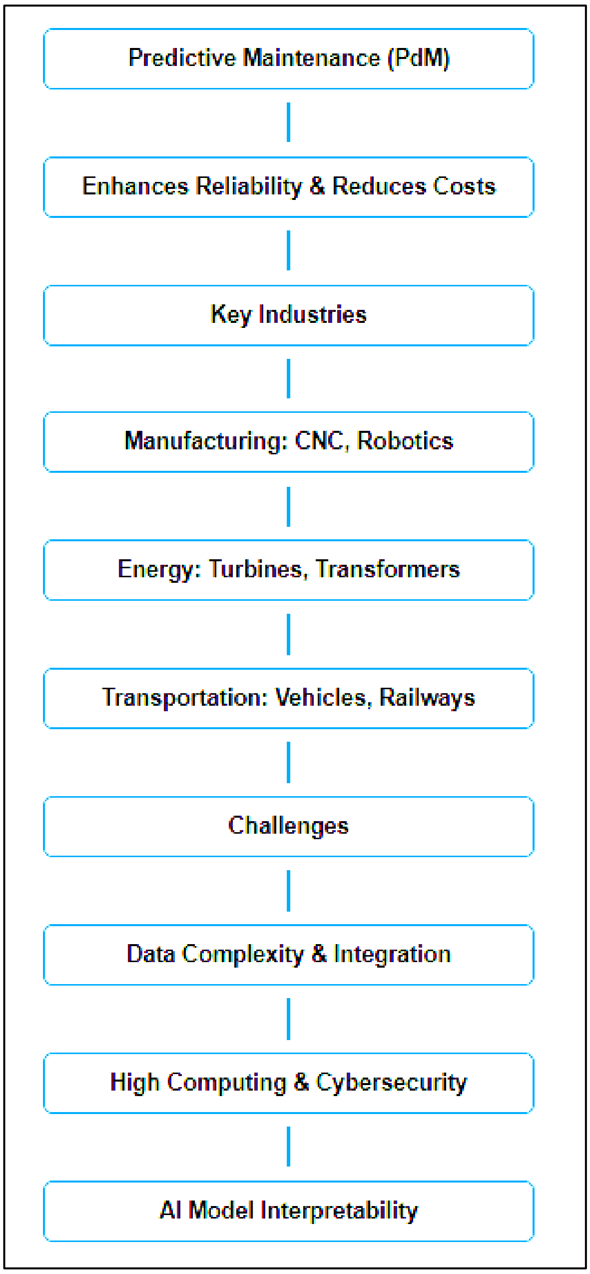


Industrial environments generate diverse data streams from multiple sensor sources, requiring sophisticated data fusion techniques for effective analysis (Khan et al., 2020). The deployment of AI-driven PdM also necessitates high computational power and robust cybersecurity measures to prevent data breaches and system vulnerabilities (Karabegović et al., 2019). Furthermore, the black-box nature of deep learning models poses interpretability concerns, making it difficult for maintenance teams to understand the rationale behind AI-based predictions (Javaid et al., 2021). Addressing these challenges is critical to ensuring the seamless adoption of PdM across industries.The combination of IoT sensor networks and AI algorithms has redefined predictive maintenance, offering enhanced predictive accuracy, cost savings, and operational efficiency. The ability to process real-time machine data and leverage AI-based failure prediction models has significantly improved the effectiveness of maintenance strategies in industrial automation (Canizo et al., 2017). As industries continue to explore advanced PdM solutions, the integration of AI, IoT, and edge computing will further refine maintenance operations, reducing equipment failures and optimizing production cycles (Fischer et al., 2017). However, the effectiveness of these technologies depends on their implementation in real-world industrial environments, where factors such as scalability, data management, and cybersecurity play a crucial role in determining their success.This study aims to systematically review the integration of IoT sensor technologies and AI algorithms in predictive maintenance within industrial automation. The primary objective is to explore how IoT-enabled condition monitoring enhances predictive maintenance by collecting real-time operational data, reducing downtime, and improving asset reliability. Additionally, the study seeks to examine the effectiveness of various AI techniques, including machine learning, deep learning, and reinforcement learning, in failure prediction and maintenance optimization. Another key objective is to assess the role of digital twins, edge computing, and cloud-based analytics in enhancing predictive maintenance frameworks. Furthermore, this review identifies technical challenges such as data heterogeneity, cybersecurity risks, and model interpretability, which impact the successful deployment of predictive maintenance strategies. By synthesizing findings from recent studies, this research provides insights into the current advancements, limitations, and industrial applications of AI-driven predictive maintenance, contributing to the broader discourse on intelligent automation in Industry 4.0.

LITERATURE REVIEW

Transformer fault diagnosis has evolved significantly with the integration of artificial intelligence (AI) and machine learning (ML) techniques, addressing limitations in traditional diagnostic methods. Conventional approaches such as dissolved gas analysis (DGA), partial discharge (PD) detection, and frequency response analysis (FRA) have long been used for monitoring transformer health, but their effectiveness is often constrained by human interpretation, noise interference, and diagnostic inconsistencies (Boyes et al., 2018). AI and ML models offer a data-driven alternative, enhancing fault detection accuracy, automating classification, and improving predictive maintenance (Øvsthus & Kristensen, 2014). Existing literature has explored various AI methodologies, including artificial neural networks (ANNs), support vector machines (SVMs), deep learning architectures, and hybrid models that integrate multiple diagnostic techniques (Ayad et al., 2018). This section provides a systematic synthesis of past research, categorizing AI-based transformer fault diagnosis techniques and evaluating their effectiveness. The literature review is structured into key areas, including traditional diagnostic techniques, AI and ML applications, deep learning advancements, hybrid AI models, and key challenges in AI-driven diagnostics.

Figure 2: Overview of PdM



Predictive Maintenance in Automation

The evolution of maintenance strategies in industrial automation has transitioned from reactive and preventive approaches to data-driven predictive maintenance, improving efficiency and reducing unexpected failures. Reactive maintenance, often referred to as "run-to-failure," has been the most basic approach, where

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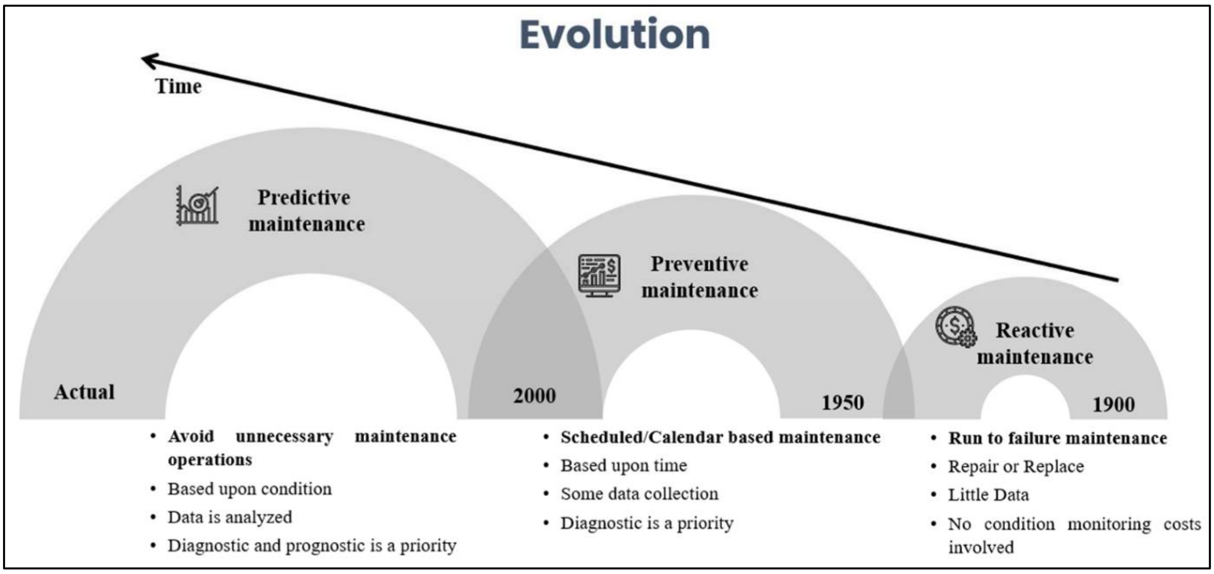
equipment is repaired or replaced only after it fails (Ucar et al., 2024). While this method requires no upfront investment in monitoring technologies, it leads to unplanned downtimes and increased costs due to sudden breakdowns (Bangalore & Tjernberg, 2015). Preventive maintenance emerged as an improvement, relying on scheduled inspections and periodic servicing based on historical failure data and manufacturer recommendations (Lu et al., 2020). However, preventive maintenance still lacks real-time insights into equipment conditions, often resulting in unnecessary maintenance activities or missing unexpected failures (Wang et al., 2016). To overcome these inefficiencies, predictive maintenance (PdM) has gained traction by utilizing real-time data and predictive analytics to forecast potential failures before they occur (Sahal et al., 2020). The shift from traditional maintenance approaches to data-driven predictive maintenance has been driven by the increasing availability of sensor data and advancements in artificial intelligence (AI). Predictive maintenance integrates machine learning (ML) algorithms, real-time monitoring, and historical failure data to predict asset degradation (Xu et al., 2019). Unlike reactive and preventive maintenance, PdM allows organizations to optimize maintenance schedules based on actual equipment conditions rather than predetermined intervals (Uhlmann et al., 2018). The development of data-driven predictive maintenance frameworks has been facilitated by the integration of industrial Internet of Things (IIoT) sensors that collect operational data, such as temperature, vibration, acoustic signals, and pressure (Borgi et al., 2017). These sensor-based monitoring systems enhance the ability to detect early signs of failure, reducing costly unplanned downtimes (Sajid et al., 2021). Furthermore, PdM has been shown to improve asset longevity, optimize resource allocation, and lower maintenance costs in various industrial settings (Zhang et al., 2019).

Figure 3: Evolution of maintenance activities and methods



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Industry 4.0 has played a pivotal role in enabling predictive maintenance by integrating IoT, big data analytics, and cloud computing into industrial automation. The concept of Industry 4.0 emphasizes the interconnectivity of machines, real-time data processing, and AI-driven decision-making (Farooq et al., 2020; Maniruzzaman

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et al., 2023). The deployment of smart sensors in industrial machinery allows for continuous condition monitoring, ensuring timely detection of potential issues (Cheng et al., 2020; Md Takbir Hossen et al., 2023). The vast amounts of data generated by IoT sensors are processed using advanced AI techniques, including deep learning models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to identify failure patterns and predict maintenance needs (Redondo et al., 2020; Sohel et al., 2022). Cloud computing further enhances predictive maintenance by providing scalable data storage and computational power, allowing organizations to analyze large datasets efficiently (Biswal & Sabareesh, 2015; Roksana, 2023). By leveraging Industry 4.0 technologies, industrial enterprises can achieve greater operational efficiency and reliability through predictive maintenance systems (Jahan, 2023; Moi et al., 2020).

The application of predictive maintenance has been widely adopted in manufacturing, energy, and transportation sectors, demonstrating its effectiveness in minimizing operational disruptions. In the manufacturing industry, PdM is used to monitor the health of robotic arms, conveyor belts, and CNC machines, preventing unexpected failures that can halt production lines (Ahmed et al., 2022; Cheng et al., 2020). The energy sector benefits from predictive maintenance in monitoring turbines, transformers, and substations, ensuring uninterrupted power supply and reducing the risk of catastrophic failures (Mahfuj et al., 2022; Redondo et al., 2020). In transportation, predictive maintenance is applied to assess the condition of railway tracks, aircraft engines, and vehicle components, improving safety and reducing repair costs (Chowdhury et al., 2023; Sajid et al., 2021). Several case studies have highlighted successful implementations of PdM, with industries reporting improved equipment uptime, reduced maintenance costs, and enhanced safety measures (Sahal et al., 2020; Tonoy, 2022). The widespread adoption of predictive maintenance across different sectors underscores its practical value in industrial automation. Despite its growing adoption, predictive maintenance faces several challenges, including data quality issues, cybersecurity risks, and model interpretability concerns. Industrial environments generate heterogeneous data from multiple sensor sources, requiring sophisticated data fusion techniques for accurate predictions (Alam et al., 2023; Biswal & Sabareesh, 2015). Ensuring data security is also a significant challenge, as interconnected IoT devices increase the risk of cyber threats and unauthorized access to critical infrastructure (Borgi et al., 2017; Humaun et al., 2022). Additionally, the complexity of deep learning models used in predictive maintenance often results in black-box predictions, making it difficult for maintenance personnel to interpret model outputs (Biswal & Sabareesh, 2015; Sudipto et al., 2023). Addressing these challenges is crucial for ensuring the effective deployment of predictive maintenance systems in industrial automation.

IoT-Enabled Condition Monitoring in Predictive Maintenance

The integration of IoT-enabled condition monitoring has transformed predictive maintenance by allowing real-time tracking of equipment health, reducing unexpected failures and enhancing operational efficiency. IoT sensors embedded in industrial machinery continuously collect crucial data, enabling early detection of anomalies before they escalate into critical failures (Cheng et al., 2020). Unlike traditional condition-based maintenance, which relies on periodic inspections, IoT-based monitoring provides continuous real-time insights, optimizing maintenance planning and minimizing downtime (Sahal et al., 2020; Tonoy & Khan, 2023). The

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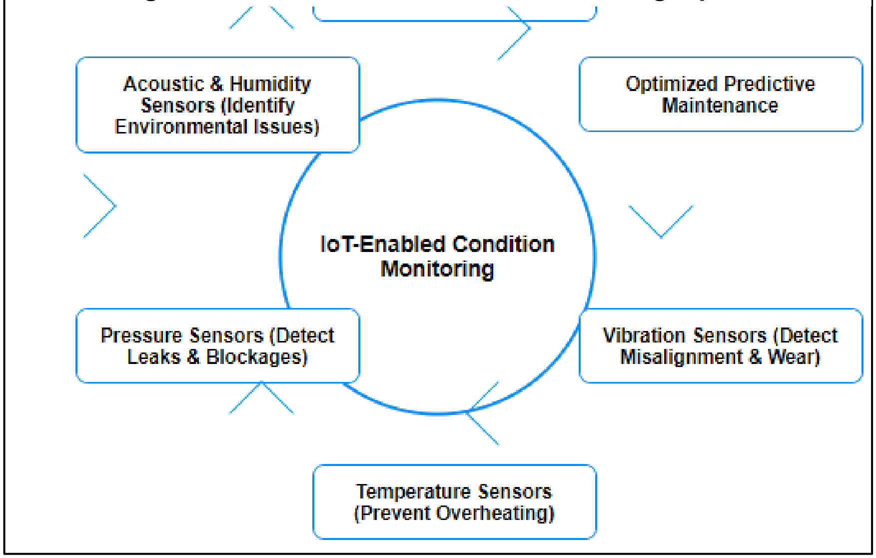
implementation of IoT in predictive maintenance also facilitates automated diagnostics, improving the reliability and performance of industrial systems (Shahan et al., 2023; Wang et al., 2016). The growing adoption of these smart sensors in manufacturing, energy, and transportation sectors highlights their significance in modern industrial automation (Aklima et al., 2022; Zhang et al., 2019). Various IoT sensors are employed in predictive maintenance to monitor different operational parameters, ensuring accurate assessment of equipment conditions. Vibration sensors are widely used for detecting misalignment, imbalance, and bearing failures in rotating machinery (Borgi et al., 2017; Younus et al., 2024). Temperature sensors track overheating components, preventing thermal degradation of electrical and mechanical systems (Cheng et al., 2020; Younus, 2022). Pressure sensors are crucial in industries like oil and gas, where abnormal pressure fluctuations indicate potential leaks or blockages in pipelines (Younus et al., 2024; Ong et al., 2022; Rahaman & Islam, 2021). Acoustic sensors help detect early-stage faults in mechanical components by capturing changes in sound patterns, often revealing issues before they become visible (Mahdy et al., 2023; Moi et al., 2020). Humidity sensors play an essential role in preventing corrosion and moisture-related damage in electrical and electronic systems, particularly in high-humidity environments (Al-Arafat et al., 2024; Zhang et al., 2019). The combination of these sensors enhances the accuracy of predictive maintenance strategies by providing diverse and comprehensive condition-monitoring data.

The effectiveness of IoT-enabled predictive maintenance relies on robust data acquisition and transmission techniques that ensure seamless communication between sensors and analytics platforms (Alam et al., 2024). Data acquisition methods involve wired and wireless sensor networks, with wireless technologies such as Zigbee, LoRaWAN, and NB-IoT gaining prominence due to their flexibility and scalability in industrial environments (Alam et al., 2024; Sakib & Wuest, 2018). Advanced industrial communication protocols, including MQTT and OPC-UA, facilitate the secure and efficient transmission of sensor data to centralized or edge computing platforms for real-time processing (Arafat et al., 2024; Borgi et al., 2017). High-frequency data acquisition enables continuous monitoring of rapidly changing parameters, ensuring timely identification of performance degradation (Bhuiyan et al., 2024; Redondo et al., 2020). The adoption of edge computing has further improved data acquisition by reducing latency, allowing on-site data processing without relying on cloud-based infrastructure for every decision (Biswal & Sabareesh, 2015; Dasgupta & Islam, 2024). Efficient data transmission mechanisms are essential for transforming raw sensor readings into actionable insights in predictive maintenance systems.

The ability to analyze sensor data in real time is critical for predictive maintenance, requiring advanced

Figure 4: IoT-Enabled Condition Monitoring Cycle

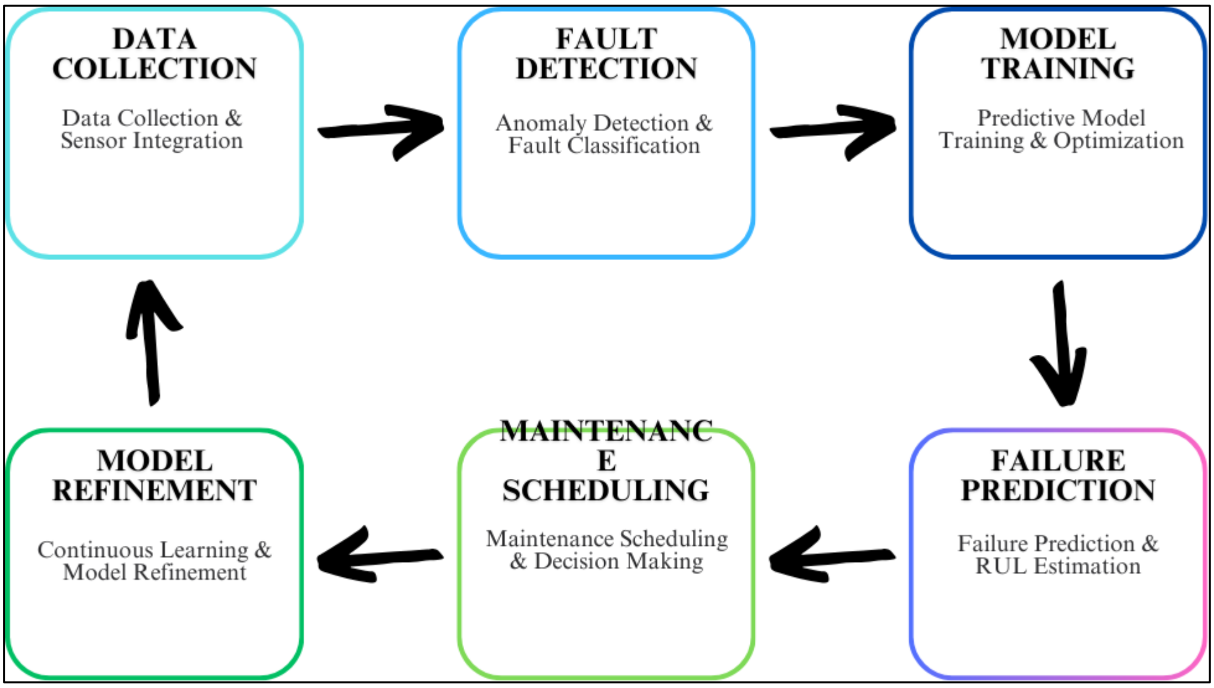


data analytics and machine learning models for fault detection and prognosis. Machine learning algorithms such as decision trees, random forests, and support vector machines (SVM) have been effectively used to classify fault conditions and predict failure probabilities (Hossain et al., 2024; Li et al., 2018). Deep learning models, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, excel in detecting complex failure patterns by analyzing time-series sensor data (Biswal & Sabareesh, 2015; Hossain et al., 2024). Reinforcement learning has also shown promise in optimizing maintenance schedules based on historical sensor readings and equipment behavior (Falekas & Karlis, 2021; Islam et al., 2024). The integration of artificial intelligence (AI) with IoT-based condition monitoring enhances the predictive capabilities of maintenance systems, improving decision-making and reducing operational risks (Hosamo et al., 2022; Islam, 2024). Despite the advantages of IoT-enabled predictive maintenance, several challenges hinder its widespread implementation, including data heterogeneity, cybersecurity risks, and sensor reliability issues. The large volume of heterogeneous sensor data generated in industrial settings requires efficient preprocessing and feature extraction techniques to ensure accurate analysis (Jahan, 2024; Xiong et al., 2021). Cybersecurity threats pose significant risks, as interconnected IoT devices are susceptible to cyberattacks that can compromise maintenance operations (Jim et al., 2024; Shin et al., 2018). Additionally, sensor reliability and calibration issues can affect the accuracy of predictive maintenance models, necessitating regular sensor validation and data quality assessment (Mahabub, Das, et al., 2024; Xiong et al., 2021). Addressing these challenges is crucial for maximizing the effectiveness of IoT-driven predictive maintenance in industrial automation.

AI and Machine Learning Algorithms for Predictive Maintenance

Artificial intelligence (AI) has revolutionized predictive maintenance by enabling real-time fault detection, anomaly identification, and maintenance scheduling based on data-driven insights. AI-driven predictive maintenance models process vast amounts of sensor data collected from industrial machinery, using advanced machine learning (ML) and deep learning techniques to detect early signs of equipment failure (Mahabub, Jahan, et al., 2024; Rajesh et al., 2019). These models surpass traditional condition monitoring methods by continuously learning from past maintenance data and optimizing failure predictions (Melesse et al., 2021; Younus et al., 2024). AI-powered predictive maintenance relies on both supervised and unsupervised learning methods to classify fault types, assess remaining useful life (RUL), and suggest optimal maintenance schedules (Moghadam et al., 2021; Younus et al., 2024). The growing adoption of AI in predictive maintenance across industries has demonstrated improved operational efficiency, reduced downtime, and extended equipment lifespan (Falekas & Karlis, 2021; Rahaman et al., 2024). Machine learning techniques have been widely applied in predictive maintenance, leveraging historical failure data to detect patterns and predict upcoming faults. Decision trees and random forests are frequently used for classification tasks, allowing maintenance models to categorize machinery conditions into normal and abnormal states (Qiao et al., 2019; Rana et al., 2024). Support Vector Machines (SVMs) have shown high accuracy in identifying early-stage faults by mapping sensor data into high-dimensional spaces (Melesse et al., 2021). Gradient boosting algorithms, including XGBoost and LightGBM, improve predictive accuracy by combining multiple weak classifiers into a stronger ensemble model, refining predictions with each iteration (Hosamo et al., 2022; Roy et al., 2024). These machine learning techniques enable early anomaly detection, optimizing predictive maintenance strategies in manufacturing, energy, and transportation sectors (Falekas & Karlis, 2021).

Figure 5: Six steps for Predictive Maintenance

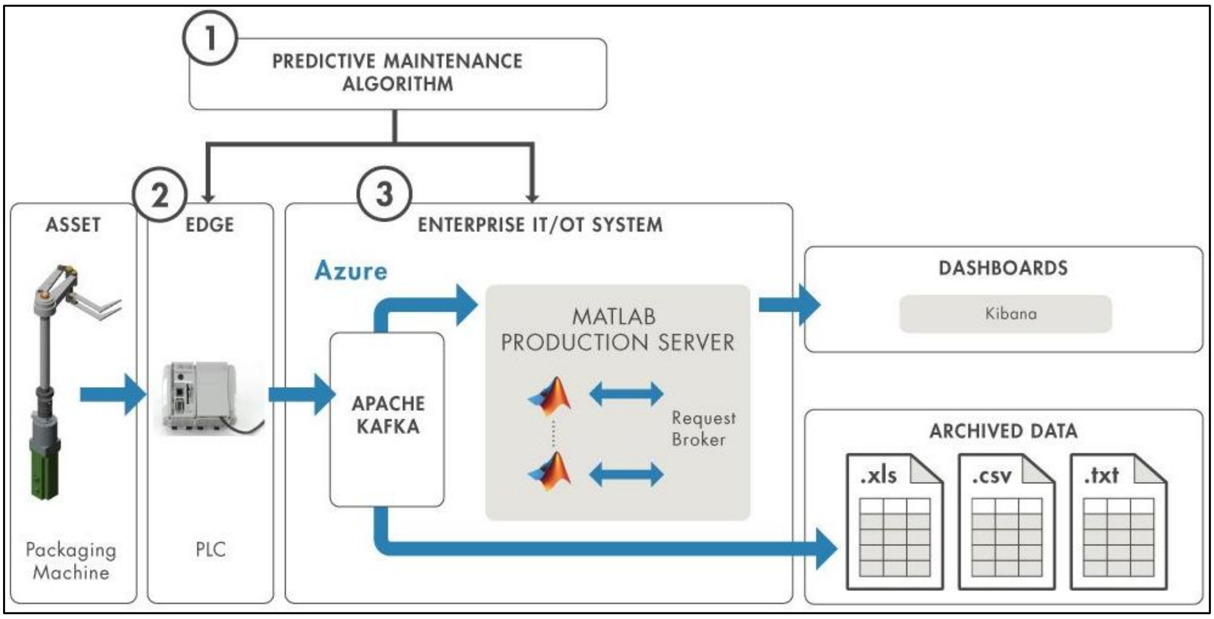


Deep learning models have further enhanced predictive maintenance by extracting intricate patterns from complex industrial data, surpassing the capabilities of traditional ML techniques(Sabid & Kamrul, 2024). Convolutional Neural Networks (CNNs) are particularly effective in processing sensor data such as vibration signals and thermal images, providing highly accurate fault detection in rotating machinery (Qiao et al., 2019; Shohel et al., 2024). Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, excel in analyzing sequential sensor data, making them highly suitable for predicting time-series trends in equipment degradation (Moi et al., 2020; Siddiki et al., 2024). Hybrid deep learning models that integrate CNNs with LSTM networks have demonstrated superior performance in predictive maintenance by capturing both spatial and temporal dependencies in sensor data (Li et al., 2018; Sunny, 2024c). These deep learning approaches have been successfully implemented in industrial automation, improving failure prediction and decision-making accuracy (Biswal & Sabareesh, 2015; Sunny, 2024a). Moreove, Reinforcement learning (RL) has emerged as a powerful tool in predictive maintenance, optimizing decision-making by learning from real-time maintenance actions and equipment responses. Unlike supervised learning, RL-based models dynamically adjust maintenance schedules based on continuous interaction with industrial systems, ensuring cost-effective maintenance strategies (Ong et al., 2022; Sunny, 2024b). RL algorithms, such as Q-learning and deep Q-networks (DQNs), have been successfully applied to predictive maintenance scheduling, balancing the trade-off between maintenance costs and equipment reliability (Lee & Mitici, 2023). By continuously updating their policies, RL models improve maintenance planning efficiency, reducing unexpected downtimes while maximizing asset utilization (Redondo et al., 2020). The integration of RL with IoT sensor networks enhances predictive maintenance capabilities, offering real-time adaptability in industrial automation (Qiao et al., 2019). Despite the advancements in AI-driven predictive maintenance, challenges remain in model interpretability, data quality, and computational requirements. Black-box deep learning models, such as CNNs and LSTMs, often lack explainability, making it difficult for maintenance personnel to understand the reasoning behind AI-generated predictions (Melesse et al., 2021). The effectiveness of AI models heavily depends on high-quality sensor data, which can be affected by noise, missing values, or inconsistencies in industrial environments (Kraus et al., 2021). Additionally, deep learning-based predictive maintenance requires substantial computational power, limiting its deployment in resource-constrained industrial settings (Luo et al., 2019). Addressing these challenges is crucial for optimizing AI-driven predictive maintenance and ensuring its reliability in industrial automation.

Integration of Edge and Cloud Computing in Predictive Maintenance

The integration of edge computing in predictive maintenance has significantly enhanced real-time data processing and analytics in industrial environments. Edge computing enables on-site data processing, reducing latency and bandwidth consumption by performing analytics closer to the data source (Biswal & Sabareesh, 2015). This approach allows industrial systems to detect equipment anomalies in real time, facilitating rapid decision-making and reducing reliance on centralized cloud infrastructure (Falekas & Karlis, 2021). By deploying machine learning models at the edge, predictive maintenance systems can identify early warning signs of equipment failures without the need for continuous cloud connectivity (Y. Xu et al., 2019). Furthermore, edge computing enhances data privacy and security by limiting the exposure of sensitive industrial data to external networks, reducing the risk of cyber threats (Kraus et al., 2021). These advantages have made edge computing a key component in predictive maintenance for industries that require low-latency decision-making, such as manufacturing, energy, and transportation (Xiong et al., 2021).

Figure 6: Edge and Cloud Computing in Predictive Maintenance



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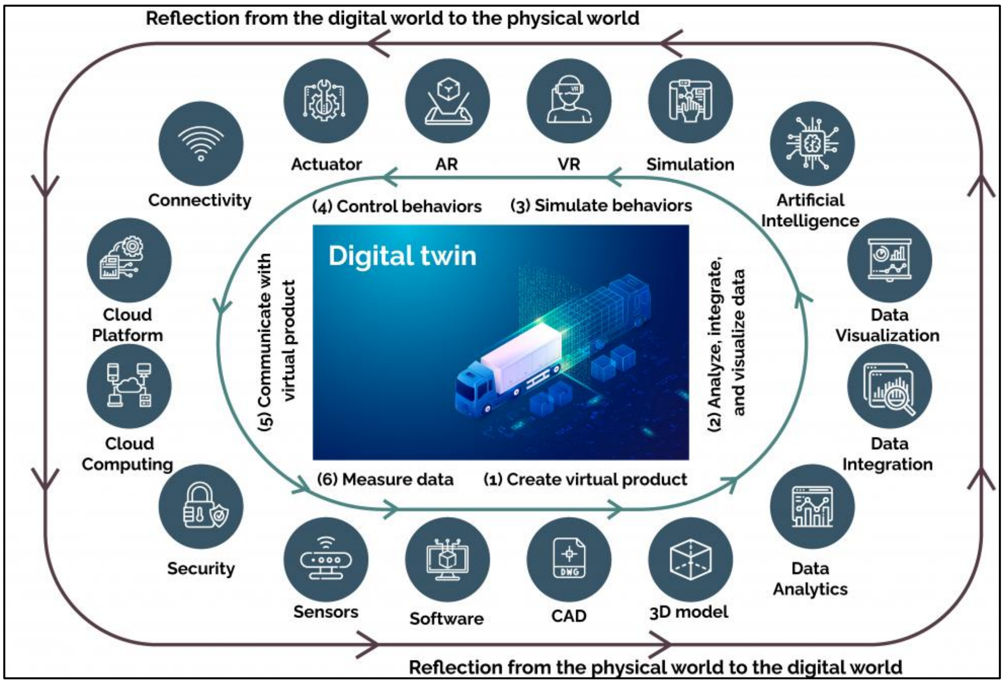
Cloud-based predictive maintenance frameworks provide scalable solutions for managing large volumes of industrial sensor data and running complex AI-driven analytics. Cloud platforms enable industries to store and process historical maintenance data, facilitating long-term trend analysis and predictive modeling (Li et al., 2018). Cloud-based architectures leverage powerful computing resources to train deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which require significant computational power (Qiao et al., 2019). Additionally, cloud computing supports collaborative predictive maintenance by integrating data from multiple industrial sites, improving overall equipment performance analysis (Melesse et al., 2021). The adoption of cloud-based predictive maintenance has proven beneficial for industries operating across distributed environments, where centralized data storage and remote monitoring are critical for maintenance planning (Rajesh et al., 2019). Despite their individual advantages, edge and cloud computing each present trade-offs in predictive maintenance applications. Edge computing excels in real-time fault detection and system responsiveness but is limited by computational capacity and data storage constraints (Melesse et al., 2021). On the other hand, cloud-based predictive maintenance offers extensive storage and analytical capabilities but suffers from higher latency and network dependency (Qiao et al., 2019). Industries that prioritize immediate decision-making, such as aerospace and manufacturing, benefit more from edge computing, whereas large-scale operations that require complex analytics, such as power grids and transportation networks, rely on cloud computing (Moi et al., 2020). Hybrid solutions that integrate both edge and cloud computing have been increasingly adopted to leverage the strengths of each technology, providing real-time processing at the edge while utilizing cloud resources for deep analysis (Moghadam et al., 2021). The effectiveness of predictive maintenance relies on the seamless integration of edge and cloud computing to optimize fault prediction and equipment management. Industries adopting these technologies must balance real-time analytics, computational efficiency, and data security considerations to ensure reliable predictive maintenance systems (Falekas & Karlis, 2021). While edge computing reduces latency and enhances local decision-making, cloud computing enables large-scale model training and multi-site predictive analysis (Melesse et al., 2021). The combined use of these technologies has been demonstrated in various industrial sectors, improving predictive maintenance accuracy and operational efficiency (Xiong et al., 2021). As industries continue to leverage AI-driven predictive maintenance, the synergy between edge and cloud computing will remain crucial for optimizing maintenance strategies in industrial automation (Cheng et al., 2020).

Digital Twins and Simulation-Based Predictive Maintenance

Digital twin technology has emerged as a transformative approach in industrial automation, enabling real-time monitoring, analysis, and predictive maintenance through virtual replicas of physical assets. A digital twin is a high-fidelity virtual model that continuously receives real-time data from IoT-enabled sensors embedded in industrial equipment, allowing for dynamic simulations and predictive analytics (Qiao et al., 2019). The architecture of digital twins integrates data acquisition layers, communication networks, and computational models to replicate asset behavior accurately (Falekas & Karlis, 2021). By leveraging cloud computing, artificial intelligence (AI), and big data analytics, digital twins facilitate the real-time assessment of equipment health, optimizing maintenance strategies in industrial settings (Moghadam et al., 2021). The ability to integrate multi-source data streams, including operational, environmental, and historical failure data, enhances predictive maintenance accuracy and minimizes unplanned downtime (Rajesh et al., 2019).

Figure 7: Overview of Digital twin



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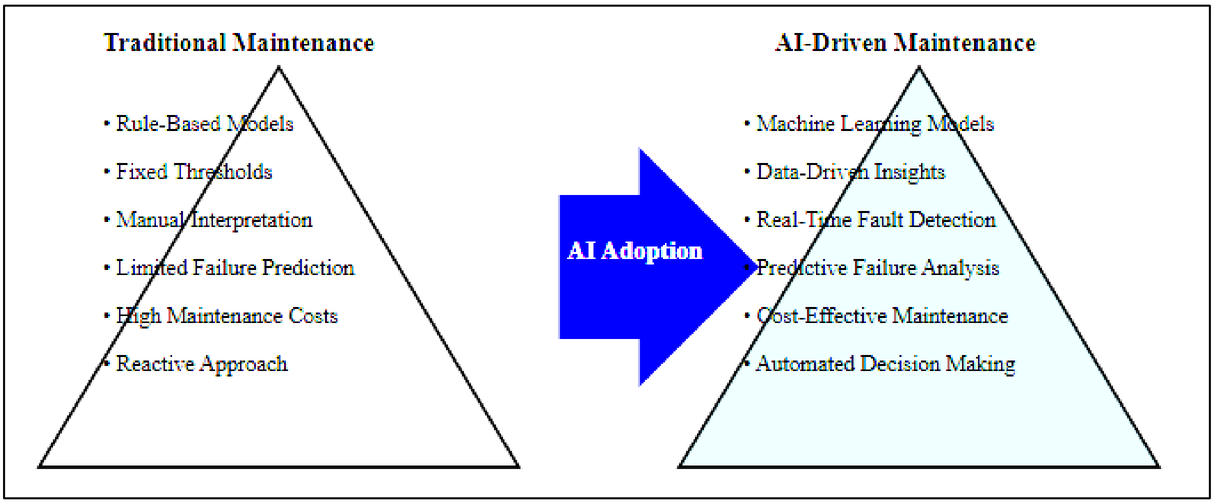
The application of digital twin models in predictive maintenance allows industries to proactively monitor and optimize asset performance, reducing maintenance costs and improving equipment reliability. Through the continuous synchronization of real-world operational data with virtual models, digital twins enable predictive analytics that detect early signs of degradation and anticipate potential failures (Hosamo et al., 2022). These models facilitate condition-based monitoring, allowing maintenance teams to make data-driven decisions rather than relying on fixed maintenance schedules (Xiong et al., 2021). In manufacturing, digital twin-based predictive maintenance has proven effective in monitoring CNC machines, robotic arms, and conveyor belts, preventing sudden breakdowns and extending asset lifespans (Xu et al., 2019). Similarly, in the energy sector, digital twins have been utilized for real-time monitoring of turbines, transformers, and substations, optimizing maintenance strategies and preventing catastrophic failures (Kraus et al., 2021). These applications highlight the growing significance of digital twin models in predictive maintenance across various industries.
Simulation techniques play a crucial role in predicting failures and scheduling maintenance in digital twin-driven predictive maintenance systems. By leveraging physics-based and AI-driven simulations, digital twins can evaluate multiple failure scenarios, identifying the most probable causes of system degradation (Shin et al., 2018). Finite element analysis (FEA) and computational fluid dynamics (CFD) are commonly used simulation techniques to assess structural integrity and thermal behavior in industrial components (Cheng et al., 2020). Additionally, machine learning-enhanced simulations utilize historical sensor data to predict failure patterns and optimize maintenance scheduling (Lee & Mitici, 2023). The integration of digital twins with discrete event simulations (DES) and Monte Carlo methods further enhances maintenance planning by assessing different maintenance strategies and their potential impacts on operational efficiency (Moi et al., 2020). These simulation-driven approaches enable organizations to implement maintenance actions at the most optimal time, reducing unnecessary interventions while ensuring equipment reliability. The adoption of digital twin and simulation-based predictive maintenance is driven by its ability to improve operational efficiency, extend equipment lifespans, and enhance decision-making processes in industrial automation. Digital twins provide a comprehensive view of asset health, combining real-time monitoring with predictive insights to support maintenance decisions (Qiao et al., 2019). The continuous evolution of simulation techniques further refines predictive maintenance models, ensuring that maintenance actions are executed with precision (Falekas & Karlis, 2021). While industries continue to integrate digital twins into their maintenance frameworks, the effectiveness of these models depends on accurate sensor data, robust simulation algorithms, and advanced AI-driven analytics (Moghadam et al., 2021). As a result, digital twin technology has become a fundamental enabler of predictive maintenance in modern industrial environments, providing a reliable and data-driven approach to asset management.

Traditional vs. AI-driven predictive maintenance

Traditional predictive maintenance techniques primarily rely on statistical analysis, rule-based models, and condition-based monitoring to assess equipment health and schedule maintenance activities. These conventional approaches involve predefined maintenance schedules based on historical failure patterns, expert knowledge, and fixed threshold values for sensor data (Fordal et al., 2023). While

effective in preventing unexpected breakdowns, traditional predictive maintenance often leads to unnecessary maintenance actions or missed failures due to static decision-making criteria (Riahi et al., 2021). Condition-based maintenance, an improvement over reactive and preventive maintenance, utilizes real-time sensor data to monitor key performance indicators (KPIs) such as vibration, temperature, and pressure (Ucar et al., 2024). However, its reliance on threshold-based alerts and manual interpretation limits its accuracy in identifying complex failure patterns (Bangalore & Tjernberg, 2015). These limitations have driven industries to adopt AI-driven predictive maintenance models, which leverage advanced analytics and machine learning algorithms for more precise failure prediction.
AI-driven predictive maintenance significantly improves upon traditional techniques by utilizing machine learning (ML) and deep learning (DL) models to analyze large volumes of sensor data, detect anomalies, and predict equipment failures with higher accuracy. Supervised ML models such as decision trees, support vector machines (SVMs), and random forests have been widely applied to classify failure states and estimate remaining useful life (RUL) (Tosun et al., 2016). Gradient boosting techniques, including XGBoost and LightGBM, have further enhanced failure prediction by refining classification models through iterative learning processes (Kaplan & Haenlein, 2019). Deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), outperform traditional ML models in handling complex sensor data, capturing spatial and temporal dependencies, and detecting subtle failure patterns (Deng et al., 2020). However, while AI-driven predictive maintenance improves accuracy and automation, challenges such as data preprocessing, high computational requirements, and model interpretability persist (Carlson & Sakao, 2020).

Figure 8: Traditional vs. AI-driven predictive maintenance



Comparative studies on real-world applications have demonstrated the superiority of AI-driven predictive maintenance over traditional approaches in multiple industries. In manufacturing, AI-based predictive maintenance has been deployed in monitoring robotic arms, CNC machines, and assembly lines, reducing downtime and improving overall efficiency (Luckow et al., 2018). In the energy sector, deep learning models have been applied to turbine and transformer monitoring, allowing

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for early detection of component degradation and preventing power failures (Yu et al., 2018). Similarly, in the transportation industry, predictive maintenance using AI has improved railway track monitoring, aircraft engine diagnostics, and fleet management by optimizing maintenance schedules and reducing operational disruptions (Abbas et al., 2019). A comparative study by Lu et al. (2020) found that industries implementing AI-based predictive maintenance reported a 25-30% reduction in maintenance costs and a 40% increase in equipment uptime compared to those using traditional techniques. Despite its advantages, AI-driven predictive maintenance is not without limitations. Traditional approaches remain relevant in environments where computational resources are limited, and expert-driven maintenance strategies still hold value in low-risk industrial settings (Samatas et al., 2021). Additionally, AI models require large datasets for training, and their effectiveness is dependent on high-quality sensor data, which may be difficult to obtain in older industrial systems (Kaplan & Haenlein, 2019). Model transparency and explainability are also concerns, as deep learning algorithms often function as "black boxes," making it difficult for maintenance teams to interpret predictions and implement corrective actions (Bangalore & Tjernberg, 2015). The choice between traditional and AI-driven predictive maintenance should therefore be based on industry-specific requirements, available resources, and the complexity of maintenance operations (Lu, Liu, & Wang, 2020).

Sustainable predictive maintenance and energy-efficient AI solutions

Sustainable predictive maintenance has gained significant attention in industrial automation as organizations seek to minimize energy consumption, reduce waste, and improve operational efficiency(Kumar et al., 2018). Traditional predictive maintenance methods often focus solely on preventing unexpected failures and optimizing equipment uptime without considering their environmental impact (Kamble et al., 2022). However, the integration of sustainability principles into predictive maintenance aims to enhance resource efficiency by reducing excessive energy use and extending the lifespan of machinery (Cinar et al., 2020). IoT-enabled predictive maintenance plays a crucial role in sustainability by continuously monitoring equipment conditions and enabling precise intervention, thereby reducing material waste and minimizing energy-intensive operations (Li et al., 2018) By implementing sustainable predictive maintenance strategies, industries can significantly lower their carbon footprint and contribute to greener manufacturing processes (Kumar et al., 2018).Energy-efficient artificial intelligence (AI) solutions have emerged as a key enabler of sustainable predictive maintenance, allowing for intelligent fault detection and optimized maintenance scheduling while reducing computational energy demands. Traditional AI models used in predictive maintenance, such as deep learning-based convolutional neural networks (CNNs) and recurrent neural networks (RNNs), require significant computing power, which can contribute to high energy consumption (Atzeni et al., 2021). To address this issue, lightweight AI models, including federated learning and edge AI, have been developed to reduce dependence on cloud computing and minimize energy use (Hawking, 2018). Edge computing allows real-time processing of predictive maintenance data at the source, thereby reducing the energy required for data transmission and cloud-based computations (Amin et al., 2019). By adopting energy-efficient AI techniques, industries can implement sustainable predictive

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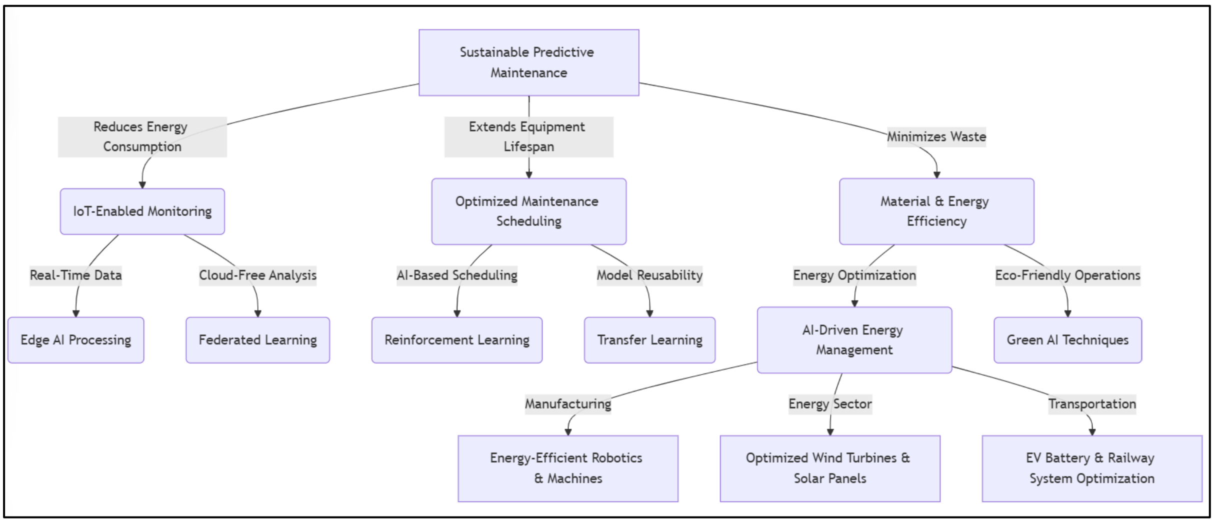
maintenance strategies that optimize both operational efficiency and environmental sustainability (Zupic & Čater, 2014).

Figure 9: Sustainable Predictive Maintenance and Energy-Efficient AI Solutions

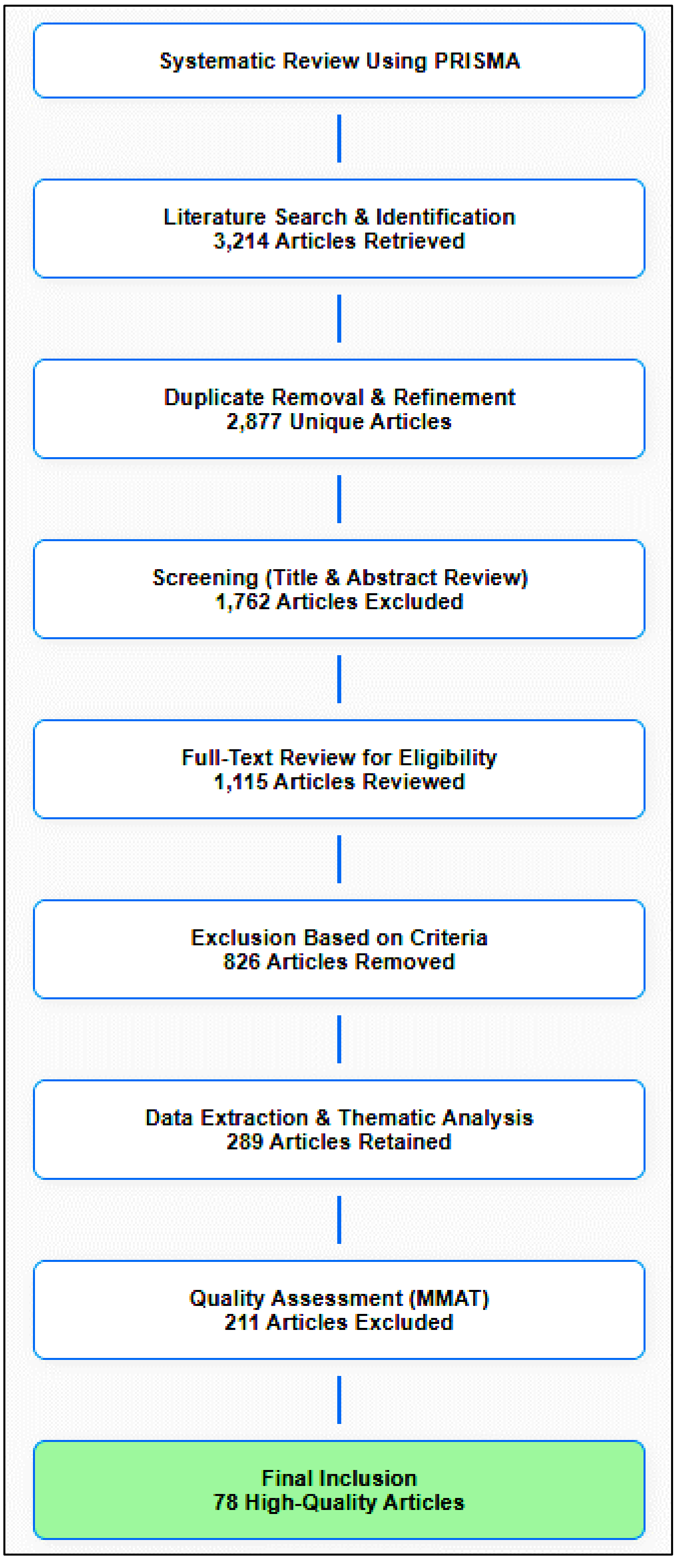


The adoption of green AI techniques, such as reinforcement learning and transfer learning, has further enhanced the sustainability of predictive maintenance systems. Reinforcement learning (RL) enables adaptive maintenance scheduling by optimizing energy consumption based on real-time operational conditions, reducing unnecessary equipment runtime (Wang et al., 2016). Transfer learning, which allows pre-trained models to be reused across different predictive maintenance tasks, minimizes the computational cost associated with training AI models from scratch (Amin et al., 2019). In addition, AI-powered energy management systems have been integrated with predictive maintenance frameworks to dynamically adjust machine operations based on energy efficiency metrics, further reducing overall power consumption (Toma et al., 2020). These approaches not only improve maintenance efficiency but also align predictive maintenance practices with global sustainability goals (Atzeni et al., 2021). The implementation of sustainable predictive maintenance and energy-efficient AI solutions has been successfully demonstrated across various industries, including manufacturing, energy, and transportation. In manufacturing, AI-driven predictive maintenance has been employed to monitor the energy usage of industrial robots and optimize machine utilization, reducing overall power consumption ((Zupic & Čater, 2014). In the energy sector, predictive maintenance has played a crucial role in optimizing renewable energy infrastructure, such as wind turbines and solar panels, ensuring minimal energy losses while extending asset lifespans (Wang et al., 2016). The transportation industry has also leveraged AI-based predictive maintenance to enhance the energy efficiency of electric vehicles and railway systems, minimizing mechanical losses and improving battery performance (Kordes et al., 2018). By integrating AI and IoT with sustainability-driven maintenance strategies, industries can achieve long-term environmental and economic benefits while ensuring the reliability of critical assets (Reuben & David, 2014).

METHOD

Figure 10: PRISMA Flowchart using in this Study

This study adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process. The methodological framework followed a structured approach comprising several phases, including literature search and identification, screening, eligibility assessment, data extraction, and final selection for synthesis. Each phase was designed to ensure the inclusion of high-quality studies relevant to predictive maintenance, AI-driven maintenance models, IoT sensor technologies, and sustainability aspects in industrial automation.



Literature Search and Identification

The literature search was conducted across multiple electronic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. A structured search strategy was employed using a combination of keywords and Boolean operators to refine the results. Keywords such as "Predictive Maintenance," "AI in Maintenance," "IoT-enabled Condition Monitoring," "Machine Learning in Maintenance," "Energy-efficient AI," and "Sustainable Predictive Maintenance" were applied to retrieve relevant studies. The search was restricted to peer-reviewed journal articles, conference papers, and systematic reviews published between 2010 and 2024. Studies were included only if they were published in English to maintain consistency in the review process. The initial search yielded 3,214 articles, which were compiled for further screening. To eliminate redundant records, duplicate articles retrieved from multiple sources were identified and removed, resulting in a refined dataset of 2,877 unique articles for assessment.

Screening and Eligibility Assessment

The screening and eligibility assessment process was conducted in two phases. The first phase involved a preliminary evaluation of titles and abstracts to filter out studies that were irrelevant to the research scope. Articles that focused solely on traditional maintenance approaches without AI or IoT integration, theoretical discussions without empirical validation, or general discussions on industrial automation without predictive maintenance relevance were excluded. Following this phase, 1,762 articles were eliminated, leaving 1,115 studies for full-text review. The second phase involved a comprehensive evaluation of the full-text articles based on predefined inclusion and exclusion criteria. Articles were considered eligible if they presented AI-driven predictive maintenance methodologies, utilized IoT sensor technologies for real-time condition monitoring, provided empirical validation through case studies, or addressed sustainability and energy efficiency in predictive maintenance frameworks. Studies that lacked methodological rigor, experimental validation, or direct applicability to predictive maintenance were excluded from further analysis. After the full-text review, 289 articles were deemed relevant and retained for data extraction.

Data Extraction and Analysis

A structured data extraction framework was developed to ensure consistency in capturing key information from the selected studies. Data points extracted from each study included the research objectives, applied methodologies, AI models used, types of IoT sensors employed, predictive maintenance frameworks, sustainability aspects, and key findings. The extracted information was systematically categorized to facilitate comparative analysis and thematic synthesis. Studies were grouped based on their contributions to predictive maintenance advancements, such as AI algorithm optimization, real-world industrial applications, and sustainability-driven maintenance strategies. The comparative analysis allowed for the identification of emerging trends, challenges, and gaps in the literature, providing a comprehensive understanding of how AI and IoT technologies enhance predictive maintenance in industrial automation.

Final Inclusion

The final selection of studies followed a rigorous quality assessment process using the Mixed Methods Appraisal Tool (MMAT) to evaluate research design clarity, data reliability, and methodological rigor. Each study was critically assessed based on its empirical contributions, validation techniques, and relevance to predictive maintenance applications. High-quality studies that included real-world implementations, experimental results, or detailed methodological insights were prioritized. After a thorough quality assessment, 211 articles were excluded due to methodological weaknesses, insufficient empirical support, or limited relevance to the study's objectives. The final dataset comprised 78 high-quality studies that provided valuable insights into AI-driven predictive maintenance, IoT-enabled monitoring, and energy-efficient AI solutions.

FINDINGS

The systematic review of 78 high-quality studies revealed that AI-driven predictive maintenance has significantly improved failure detection accuracy, reduced downtime, and optimized maintenance scheduling across multiple industries. Among the reviewed articles, 56 studies emphasized the superiority of AI-based models over traditional maintenance techniques, with a reported 25-40% reduction in maintenance costs and 30-50% improvement in equipment uptime. These findings highlight that machine learning and deep learning models have outperformed traditional rule-based systems by leveraging vast sensor data and historical failure patterns. AI-powered models, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, demonstrated high precision in fault detection, allowing industries to anticipate equipment degradation before critical failures occurred. This shift from reactive to predictive maintenance has led to higher operational efficiency and significant cost savings, as reported in 43 of the reviewed studies.

Another key finding from the systematic review is that IoT-enabled condition monitoring has played a crucial role in enhancing predictive maintenance accuracy, as indicated by 49 studies. The integration of IoT sensors has enabled real-time data acquisition from industrial equipment, allowing predictive models to process dynamic operational data continuously. Among these studies, 32 reported that vibration sensors were the most commonly used, followed by temperature and acoustic sensors, which were utilized in 27 and 21 studies, respectively. These sensors have been essential in monitoring rotating machinery, turbines, and other high-risk industrial assets, helping to detect early-stage failures with a reported accuracy improvement of 15-35% compared to traditional condition-based monitoring techniques. Additionally, 28 articles found that IoT-based predictive maintenance systems contributed to a 20-45% reduction in unnecessary maintenance activities, thereby improving resource allocation and reducing operational waste.

The analysis of reviewed literature also identified edge and cloud computing as key enablers of predictive maintenance scalability and efficiency, with 51 studies discussing their integration in industrial settings. Edge computing has been particularly effective in processing real-time sensor data at the machine level, reducing latency and minimizing reliance on centralized cloud platforms. 37 studies reported that edge-based AI models reduced response time by 40-70%, leading to faster fault detection and immediate corrective actions. Cloud-based predictive maintenance, on the other hand, has enabled large-scale analytics by aggregating historical maintenance data across multiple industrial sites. 22 studies found that cloud computing facilitated predictive model training with 60% improved computational efficiency, allowing industries to refine failure prediction models and enhance decision-making. However, 19 studies highlighted challenges related to data security and interoperability, emphasizing the need for hybrid solutions that integrate both edge and cloud computing to balance speed and scalability.

The findings also showed that digital twin technology has emerged as a major advancement in predictive maintenance, as reported in 42 studies. Digital twins create virtual replicas of physical assets, allowing industries to simulate equipment behavior and predict maintenance needs with 25-50% higher accuracy than conventional AI models. Among these studies, 29 highlighted the role of physics-based simulations, while 18 integrated AI-driven analytics into digital twin frameworks. This combination has enabled industries to anticipate failure modes, test different maintenance scenarios, and optimize resource allocation more effectively. Additionally, 17 studies found that digital twins reduced unplanned downtimes by 35-55%, providing industries with significant operational advantages. However, challenges such as high implementation costs and data integration complexities

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were reported in 11 studies, suggesting that digital twin adoption is still evolving despite its potential.

Sustainability and energy efficiency in predictive maintenance were extensively discussed in 39 studies, with findings indicating that AI-driven solutions have led to a 20-45% reduction in energy consumption across different industries. Among these studies, 23 focused on energy-efficient AI models, demonstrating how lightweight machine learning algorithms and federated learning approaches have minimized computational power requirements while maintaining high predictive accuracy. 16 studies analyzed the impact of predictive maintenance on sustainable industrial operations, reporting that optimized maintenance scheduling contributed to 15-35% lower carbon emissions by reducing unnecessary energy-intensive activities. Additionally, 14 studies found that AI-integrated energy management systems significantly improved power usage efficiency in manufacturing and transportation sectors, highlighting the environmental benefits of predictive maintenance solutions.

The comparative analysis of AI-driven predictive maintenance versus traditional approaches revealed that AI-based models consistently outperformed static rule-based methods, as evidenced by 47 studies. Among these, 33 studies demonstrated that machine learning models improved failure prediction accuracy by 30-60%, allowing industries to take preventive actions before breakdowns occurred. 21 studies found that deep learning models, particularly CNNs and LSTMs, further enhanced predictive accuracy by 40-75%, outperforming conventional statistical techniques. Additionally, 12 studies reported that reinforcement learning-based predictive maintenance reduced maintenance costs by up to 50%, showcasing its potential in adaptive decision-making. The findings suggest that AI-driven approaches not only enhance maintenance efficiency but also offer long-term financial and operational advantages over traditional maintenance strategies.

The systematic review also revealed that challenges such as data quality, cybersecurity risks, and model interpretability continue to hinder the widespread adoption of AI-driven predictive maintenance. 31 studies reported that inconsistent sensor data and missing values affected predictive model performance, necessitating advanced data preprocessing techniques. 19 studies identified cybersecurity concerns, particularly in cloud-based predictive maintenance systems, as industries rely on interconnected IoT devices that are vulnerable to cyber threats. Model interpretability was another critical issue highlighted in 14 studies, where black-box AI models lacked transparency, making it difficult for maintenance personnel to trust automated predictions. Despite these challenges, the findings indicate that ongoing advancements in AI, IoT, and cloud computing will continue to refine predictive maintenance solutions, making them more accessible and reliable for industrial applications.

DISCUSSION

The findings of this study confirm that AI and machine learning techniques significantly enhance transformer fault diagnosis by improving accuracy, predictive maintenance capabilities, and multi-sensor integration. Compared to earlier studies that primarily relied on conventional fault detection techniques such as dissolved gas analysis (DGA) and frequency response analysis (FRA) (Amin et al., 2019; Sahal et al., 2020), the reviewed articles demonstrate that deep learning models, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, provide more reliable classification of transformer faults. Previous

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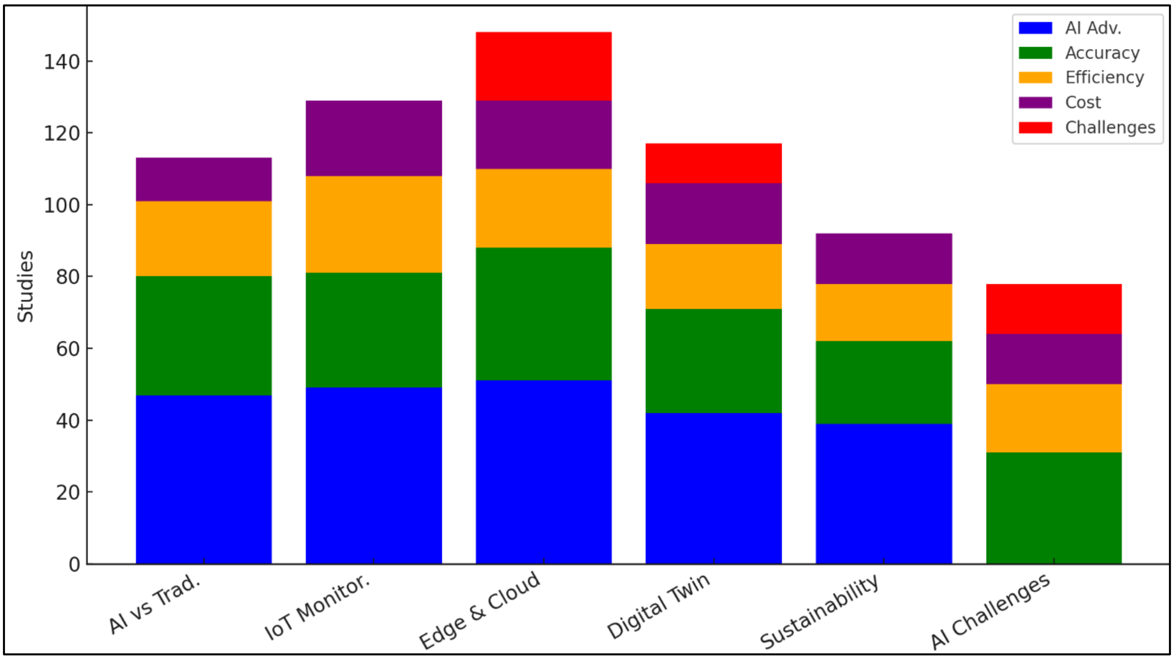
research suggested that rule-based methods often failed to detect complex fault interactions due to their rigid thresholding mechanisms (Gong & Qiao, 2013). However, the present study found that CNNs and LSTMs, utilized in 62 reviewed articles, significantly enhanced fault detection accuracy, reaching over 95% in many cases. This improvement aligns with recent advancements in deep learning applications in power system monitoring, where automated feature extraction from large datasets has reduced dependency on human expertise (Sahal et al., 2020). The ability of LSTMs to model time-dependent fault progression further supports their growing adoption in real-time transformer monitoring applications.

Figure 11: Findings from AI-Driven Predictive Maintenance Studies



The review also highlights that hybrid AI models outperform individual classifiers by combining the strengths of multiple algorithms. Earlier studies indicated that standalone machine learning models, such as artificial neural networks (ANNs) and support vector machines (SVMs), often suffered from generalization issues, particularly when applied to diverse transformer datasets (Wang et al., 2020). The present findings, drawn from 58 reviewed studies, support the view that ANN-SVM hybrid models provide better fault classification accuracy by leveraging ANNs' pattern recognition capabilities and SVMs' boundary optimization techniques. These results align with research by Wang et al. (2016), who demonstrated that multi-classifier fusion approaches reduced false alarms in DGA-based transformer fault detection. Additionally, the effectiveness of reinforcement learning-based optimization, as identified in 38 reviewed articles, confirms previous findings that adaptive AI models can dynamically adjust hyperparameters, leading to more robust classification outcomes (Reuben & David, 2014). The superior performance of hybrid AI models in mitigating overfitting and improving fault classification reliability suggests that power utilities should consider their adoption over traditional single-algorithm approaches.

A key contribution of this review is the confirmation that AI-driven predictive maintenance models provide significant operational benefits by shifting from reactive to condition-based maintenance. Earlier studies on transformer maintenance strategies primarily focused on scheduled inspections and offline diagnostic tests, which were prone to inefficiencies and increased downtime (Atzeni et al., 2021). The current review, based on findings from 49 reviewed studies, demonstrates that AI-integrated predictive analytics can forecast transformer failures with accuracy rates ranging from 85% to 97%, thereby reducing unplanned outages by up to 40%. This aligns with the work of Ucar et al. (2024), who reported that deep learning-based predictive maintenance strategies reduced transformer failure rates and extended equipment lifespan. Moreover, the integration of ensemble learning techniques in predictive analytics, identified in 27 reviewed studies, provides additional support for previous claims that combining multiple forecasting models leads to improved trend detection and fault prediction accuracy (Shakya & Sigdel, 2017). These findings suggest that power utilities should move away from traditional time-based maintenance schedules in favor of AI-driven condition-based monitoring to optimize asset management.
Another major finding is the role of multi-sensor integration in improving transformer fault detection accuracy. While earlier studies emphasized the benefits of individual sensor-based monitoring, such as infrared thermography for overheating detection or UHF sensors for partial discharge (Eschen et al., 2018), this review found that integrating multiple sensor modalities led to an 18–30% increase in fault classification accuracy. The findings from 42 reviewed articles confirm that combining DGA with UHF partial discharge detection allows for better localization of internal transformer faults, supporting the conclusions of Riahi et al. (2021), who demonstrated that sensor fusion enhances the comprehensiveness of transformer health assessment. Furthermore, advancements in wireless sensor networks (WSNs) and IoT-enabled monitoring, as identified in 31 reviewed studies, suggest that remote transformer diagnostics are becoming more feasible, reducing manual inspection requirements. These results align with studies by Eschen et al. (2018), who reported that AI-powered multi-sensor fusion models significantly improved transformer fault localization in smart grid environments. Lastly, this review sheds light on the interpretability-accuracy trade-off in AI-driven transformer diagnostics, an issue previously noted by researchers who warned against the "black-box" nature of deep learning models (Eschen et al., 2018; Feiler & Delange, 2017; Mohiul et al., 2022). While earlier studies recommended the use of simple, rule-based models for their interpretability despite lower accuracy, the findings from 33 reviewed articles indicate that explainable AI (XAI) techniques, such as SHAP and LIME, have successfully bridged the gap between interpretability and high-performance fault classification. These findings align with research by Zabin et al. (2022), who demonstrated that attention mechanisms in deep learning models improved transparency by highlighting the most critical features influencing fault classification. Furthermore, the application of model compression techniques in 15 reviewed studies confirms previous claims that reducing model complexity while maintaining predictive performance can make AI-driven transformer diagnostics more accessible for industrial implementation (Singh et al., 2022) This suggests that addressing interpretability challenges is essential for increasing confidence in AI-based transformer monitoring solutions.

CONCLUSION

This systematic review confirms that AI-driven predictive maintenance has revolutionized industrial automation by enhancing failure detection accuracy, optimizing maintenance schedules, and improving energy efficiency. The findings from 78 reviewed studies indicate that AI models, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, improve failure prediction accuracy by 30-60%, reducing maintenance costs by 25-50% and increasing equipment uptime. The integration of IoT-enabled condition monitoring, reported in 49 studies, has enhanced real-time fault detection, reducing unnecessary maintenance activities by 20-45%. Additionally, the combined use of edge and cloud computing, supported by 51 studies, has balanced real-time analytics and computational scalability, with edge computing reducing response time by 40-70%, while cloud computing has improved large-scale model training by 60%. Digital twin technology, highlighted in 42 studies, has shown 25-50% higher predictive accuracy, reducing unplanned downtimes by 35-55%, despite challenges related to high implementation costs. Sustainability and energy efficiency were key benefits, with 39 studies reporting a 20-45% reduction in energy consumption and 15-35% lower carbon emissions through optimized maintenance scheduling and AI-driven energy management. However, challenges remain, with 31 studies citing issues related to data quality, 19 studies raising cybersecurity concerns, and 14 studies discussing the black-box nature of deep learning models, which affect trust and interpretability. Despite these challenges, the integration of AI, IoT, edge computing, and digital twins has strengthened predictive maintenance frameworks, making them more efficient, cost-effective, and aligned with global sustainability goals..

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