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SMART DIAGNOSTICS IN INDUSTRIAL MAINTENANCE: A SYSTEMATIC REVIEW OF AI-ENABLED PREDICTIVE MAINTENANCE TOOLS AND CONDITION MONITORING TECHNIQUES

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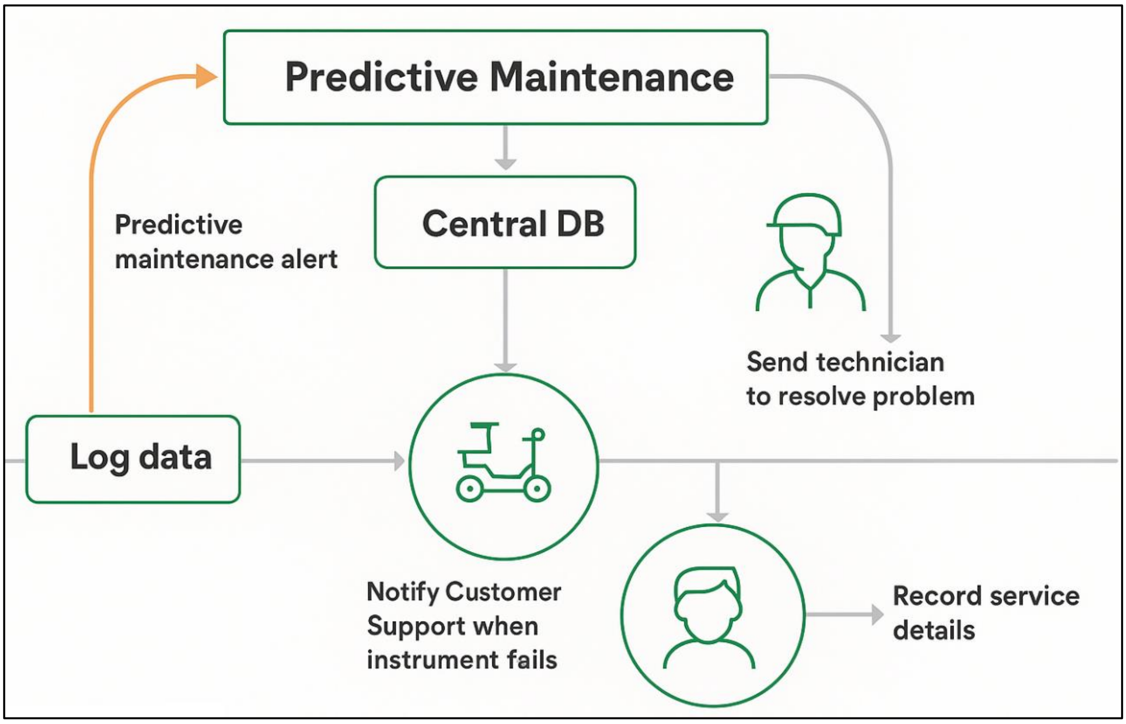
Abstract
This systematic review explores the integration of artificial intelligence (AI) in predictive maintenance and condition monitoring systems, with a focus on smart diagnostics across industrial applications. The study examines how AI technologies—including machine learning, deep learning, and hybrid models—are transforming traditional maintenance strategies by enabling automated fault detection, anomaly classification, and remaining useful life (RUL) estimation based on real-time sensor data. Drawing on a comprehensive review of 156 peer-reviewed articles published between 2015 and 2025, the research synthesizes current advancements in AI-driven maintenance tools and their applications in diverse industrial sectors such as manufacturing, energy, transportation, and utilities. Special emphasis is placed on the role of sensor technologies, including vibration, acoustic, thermal, and ultrasonic sensors, in providing the high-frequency data necessary for effective AI integration. Furthermore, the study discusses key theoretical underpinnings—including Reliability-Centered Maintenance (RCM), Prognostics and Health Management (PHM), Spatial Decision Support Systems (SDSS), and Information Systems Success Models—that frame the adoption and impact of smart diagnostics. Despite clear benefits, challenges such as data quality, model interpretability, and integration complexity remain persistent. This review contributes to both academic discourse and industrial practice by offering a comprehensive understanding of how AI technologies are redefining maintenance strategies and by identifying research gaps and opportunities for future exploration.

Keywords
Predictive Maintenance; Smart Diagnostics; Condition Monitoring; Artificial Intelligence; Industrial Internet of Things (IIoT);

INTRODUCTION

Predictive maintenance, a subset of condition-based maintenance, refers to the use of data-driven techniques and sensor-based monitoring systems to predict equipment failures before they occur, allowing timely intervention to avoid costly downtimes (Süve et al., 2021). Condition monitoring, closely associated with this approach, involves continuously or periodically assessing the health of machines through various non-invasive diagnostic tools such as vibration analysis, oil analysis, thermography, and acoustic monitoring (Panagou et al., 2022). These methodologies form the backbone of smart diagnostics—an umbrella term for intelligent technologies that assess equipment condition, predict faults, and optimize asset performance through embedded artificial intelligence (AI) capabilities (Kim et al., 2019). The global shift toward digital transformation and Industry 4.0 has amplified interest in AI-enabled maintenance systems, which leverage machine learning, deep learning, and hybrid computational models to make sense of complex operational data (Pushe et al., 2017). With the rise of the Industrial Internet of Things (IIoT), these diagnostics systems are becoming increasingly embedded within automated workflows to provide real-time insights (Heim et al., 2020). The international relevance of smart diagnostics lies in its capacity to reduce operational risks, extend machinery lifespan, and improve overall plant safety and productivity, especially in critical sectors such as energy, transportation, and manufacturing (Civerchia et al., 2017).

Figure 1: AI-Enabled Predictive Maintenance Workflow Integrating Centralized Data



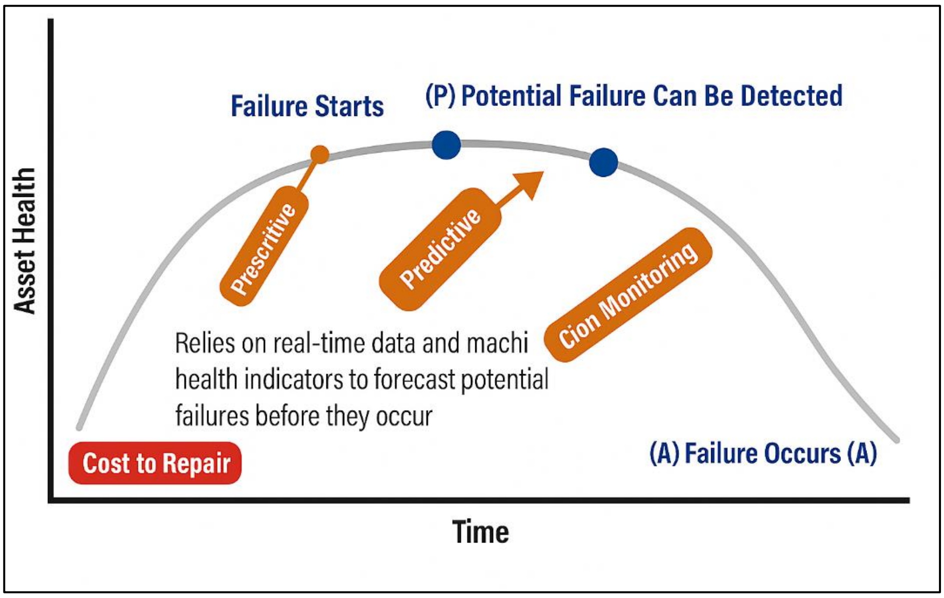
Numerous industrial reports and academic studies underscore the increasing use of AI in predictive maintenance across various sectors. For instance, in the manufacturing domain, AI-based models have been successfully deployed to detect spindle defects in CNC machines, identify wear patterns in conveyor belts, and predict anomalies in robotic arms using time-series vibration data (Wu et al., 2018). In the energy sector, machine learning algorithms have enhanced the detection of faults in gas turbines, transformers, and wind turbines through thermal imaging, acoustic signals, and SCADA data (Kanawaday & Sane, 2017). The transportation industry has also seen notable adoption, with convolutional neural networks and support vector machines being used to diagnose brake system faults and engine degradation in rail and automotive fleets. In each of these applications, data acquisition is facilitated by sensors embedded in machinery, followed by real-time or near-real-time analytics using AI-based decision-making models. Such implementations have been supported by advances in computational resources, edge computing, and cloud platforms, enabling industries to process large volumes of structured and unstructured maintenance data (Aivaliotis, Georgoulias, Arkouli, et al., 2019). The literature consistently demonstrates that these technologies can detect fault precursors earlier than traditional techniques and allow targeted maintenance interventions (Süve et al., 2021).

The integration of AI into predictive maintenance has diversified the methodologies used in condition monitoring and diagnostics. For example, supervised learning techniques such as random forests, decision trees, and k-nearest neighbors are frequently applied in industrial contexts for classifying fault types and estimating remaining useful life (Dinter et al., 2022). Meanwhile, deep learning architectures—including recurrent neural networks and convolutional neural networks—are adept at identifying complex patterns in high-dimensional sensor data streams, particularly in rotating equipment and HVAC systems (Nota et al., 2022). Hybrid approaches that combine physics-based models with AI techniques have also gained attention for enhancing prediction accuracy while maintaining interpretability (Aivaliotis, Georgoulias, & Chryssolouris, 2019). Real-time implementation of these models is made feasible through IIoT frameworks, where data from sensors, programmable logic controllers (PLCs), and enterprise resource planning (ERP) systems are aggregated for comprehensive diagnostics (Nota et al., 2022). Condition monitoring tools such as motor current signature analysis (MCSA), ultrasonic detectors, infrared thermography, and oil debris analysis are now routinely integrated with AI models for robust diagnostics (Dinter et al., 2022). These developments are increasingly supported by open-source toolkits, standardized protocols, and collaborative frameworks between academia and industry, which facilitate reproducibility and benchmarking of diagnostic algorithms across platforms (Süve et al., 2021). This study also aims to examine how AI-driven diagnostics are integrated with traditional condition monitoring tools such as vibration analysis, thermal imaging, acoustic monitoring, and oil analysis within Industrial Internet of Things (IIoT) frameworks. The objective is to uncover the mechanisms through which real-time data collected from industrial sensors are processed by AI models to generate predictive insights. The review investigates how edge computing, cloud-based analytics, and digital twin systems enable seamless integration between hardware monitoring systems and AI-based decision-making processes. This objective supports a deeper understanding of the technological ecosystem that underpins smart diagnostics and facilitates scalable, automated maintenance operations in line with Industry 4.0 principles.

Predictive Maintenance and Condition Monitoring

Predictive maintenance (PdM) and condition monitoring have become critical components in industrial operations due to their ability to optimize asset lifespan, reduce unplanned downtime, and improve operational efficiency. PdM differs from preventive maintenance by relying on real-time data and machine health indicators to forecast potential failures before they occur, allowing for targeted interventions (Dinter et al., 2022). Condition monitoring serves as the backbone of PdM by continuously tracking parameters such as temperature, vibration, acoustics, and lubricant properties through sensor integration. A variety of condition monitoring techniques have emerged, including vibration analysis, thermal imaging, oil analysis, and motor current signature analysis, each offering unique diagnostic capabilities depending on the machinery and failure type (Nota et al., 2022). Vibration-based monitoring has proven particularly effective for rotating machinery, detecting imbalances, bearing faults, and misalignments with high accuracy (Aivaliotis, Georgoulias, & Chryssolouris, 2019). Likewise, thermographic analysis is utilized for identifying hotspots and insulation failures in electrical systems, while acoustic emission monitoring excels in early fault detection in mechanical structures. Condition monitoring is further enhanced by wireless sensor networks and cloud computing platforms, which facilitate the remote acquisition and analysis of high-frequency data streams. The integration of these monitoring techniques with machine learning models has enabled a shift toward intelligent diagnostics, where failure patterns are automatically identified and remaining useful life (RUL) predictions are continuously updated (Nota et al., 2022). Studies have shown that such integrated PdM systems can reduce maintenance costs by up to 30% and unplanned downtime by over 50%, particularly in sectors like manufacturing, aerospace, and power generation (Aivaliotis, Georgoulias, & Chryssolouris, 2019). However, achieving high accuracy in PdM requires robust sensor calibration, quality historical data, and comprehensive fault libraries to train predictive models effectively (Kanawaday & Sane, 2017). Collectively, these insights underscore the foundational role of condition monitoring as a data acquisition mechanism and predictive maintenance as a decision-making process that translates sensor data into actionable outcomes.

Figure 2: Asset Health Decline Curve with Predictive Maintenance Interventions



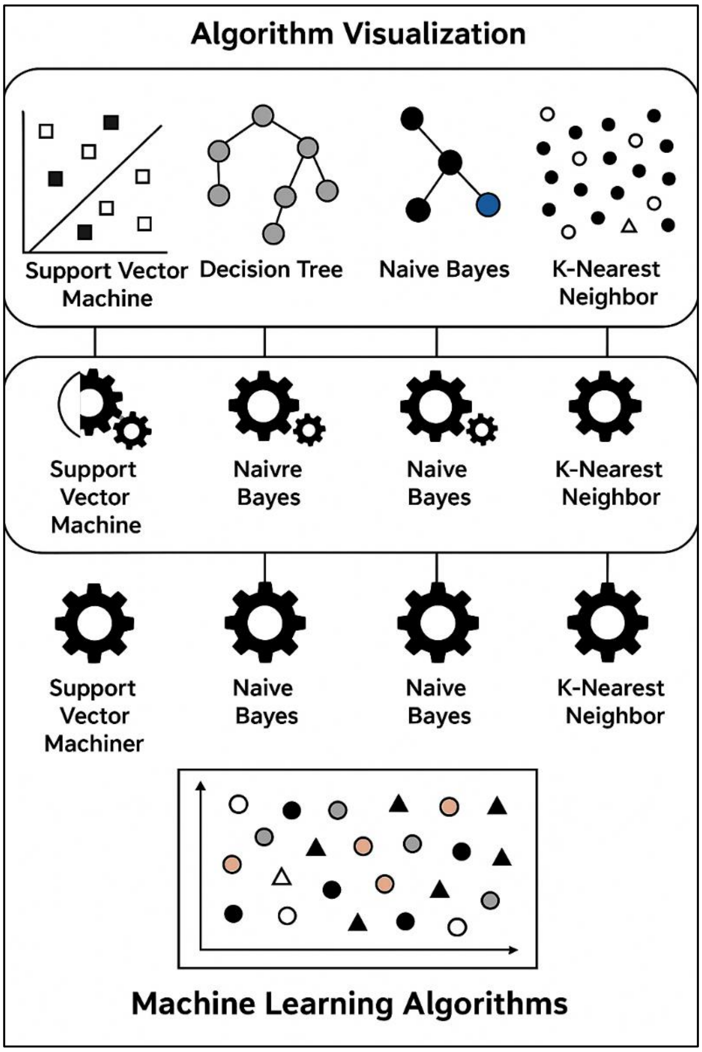
Typology of Maintenance Strategies

Maintenance strategies in industrial environments can be broadly categorized into corrective, preventive, predictive, and prescriptive approaches, each representing different levels of technological integration and operational foresight. Corrective maintenance, the most traditional form, is reactive in nature, performed only after equipment failure occurs (Classens et al., 2021). While this approach minimizes immediate costs, it often leads to extended downtimes and potential safety risks (Panagou et al., 2022). Preventive maintenance (PM), in contrast, is proactive, involving scheduled servicing and part replacements based on historical failure rates or time-based intervals, thus aiming to reduce failure probability (Muller et al., 2008). Although PM improves equipment reliability compared to corrective maintenance, it can be inefficient and costly due to unnecessary interventions on still-functioning components (Kim et al., 2019). Predictive maintenance (PdM), introduced with advancements in condition monitoring technologies, utilizes sensor data and diagnostic tools to assess equipment health in real time and forecast failures before they happen (Pushe et al., 2017). This data-driven approach improves resource utilization by reducing both unplanned outages and excessive maintenance (Heim et al., 2020). The sophistication of PdM has evolved through the adoption of statistical and AI-based methods, allowing for dynamic decision-making based on vibration, thermal, acoustic, and electrical signals (Vithanage et al., 2019). Studies across manufacturing and power sectors report PdM reducing maintenance costs by 20–30% and extending asset lifespans significantly (O'Donovan et al., 2015). These strategic differences are critical for organizations determining the cost-risk balance between reactive and proactive maintenance protocols. PdM's increasing adoption reflects a paradigm shift from schedule-based maintenance to condition-based, intelligent interventions, largely driven by Industry 4.0 and the proliferation of sensor networks and real-time analytics.

SVM, Decision Trees, KNN, Naïve Bayes

The evolution of predictive maintenance strategies has been significantly accelerated by the adoption of supervised machine learning algorithms, particularly Support Vector Machines (SVM), Decision Trees (DT), K-Nearest Neighbors (KNN), and Naïve Bayes classifiers. These algorithms are foundational in enabling data-driven maintenance strategies by learning patterns from historical failure data and classifying operational states with high accuracy. SVM is widely utilized for binary and multi-class classification problems in fault detection due to its robustness against high-dimensional datasets and its ability to find optimal separating hyperplanes (Shintemirov et al., 2009). Numerous studies have reported the effectiveness of SVM in classifying bearing faults, gearbox anomalies, and motor failures, achieving accuracies often exceeding 90% (Bacha et al., 2012). Decision Trees, on the other hand, offer a transparent rule-based approach that allows maintenance personnel to interpret the decision logic behind predictions, making them suitable for systems requiring explainability (Xin et al., 2018). DT models are especially effective in situations involving discrete condition indicators or when quick interpretability is needed in safety-critical environments. For example, studies have applied decision trees to detect compressor malfunctions and classify turbine vibration patterns with meaningful decision rules. These models are frequently combined with feature extraction techniques such as principal component analysis (PCA) or wavelet transforms to enhance performance in noisy or nonlinear datasets. The continued use of these models across manufacturing, transportation, and energy industries underscores their practicality, especially in systems where sensor data availability and computational simplicity are primary concerns.

Figure 3: Visualization of Supervised Machine Learning Algorithms for Predictive Maintenance



In parallel, the K-Nearest Neighbors (KNN) and Naïve Bayes classifiers have also demonstrated practical utility in predictive maintenance, particularly in situations requiring fast computation and low training complexity. KNN operates on a proximity-based classification approach, determining the condition class of an asset by evaluating the closest training samples in the feature space. It has been applied effectively to classify time-series vibration signals, detect rotor unbalance, and identify gearbox faults in rotating machinery (Mao et al., 2018). One limitation of KNN, however, is its sensitivity to the choice of distance metric and its computational cost in large-scale datasets; nonetheless, its simplicity makes it useful in embedded systems with constrained resources (Mao et al., 2020). Naïve Bayes classifiers, based on Bayes' theorem and assuming conditional independence among features, have also been employed in fault classification tasks with surprisingly competitive performance despite their simplicity (Xin et al., 2018). Applications include identifying early signs of bearing degradation and distinguishing between normal and abnormal temperature patterns in thermal condition monitoring (Shintemirov et al., 2009). While Naïve Bayes tends to underperform in highly correlated feature sets, it excels in systems where labeled data is scarce or where real-time fault classification is needed due to its low memory footprint and rapid inference time (Fink et al., 2020). In combination with feature selection and dimensionality reduction techniques, both KNN and Naïve Bayes have been integrated into larger ensemble and hybrid frameworks to overcome individual model limitations and improve fault detection robustness (Wang et al., 2019). These supervised learning algorithms thus form the computational foundation of modern predictive maintenance systems, facilitating the transition from scheduled preventive practices to intelligent, data-driven diagnostics that align with Industry 4.0 infrastructures.

Deep Learning Architectures: CNNs, RNNs, LSTM, Autoencoders

The adoption of deep learning architectures in predictive maintenance has revolutionized the way industrial systems manage equipment health and operational continuity. Convolutional Neural Networks (CNNs), originally developed for image processing tasks, have been widely adapted for fault diagnosis using spectrograms, vibration patterns, and thermal images (Ellefsen et al., 2019). By transforming one-dimensional sensor data into two-dimensional representations such as short-time Fourier transforms (STFT) or wavelet transforms, CNNs can capture intricate spatial dependencies in the signal data and detect abnormal patterns with high precision (Hamadache et al., 2019). In the context of rotating machinery and bearings, CNNs have been used to automatically extract hierarchical features without manual feature engineering, significantly improving diagnostic accuracy (Luo et al., 2020). Several benchmark datasets such as CWRU (Case Western Reserve University) and Paderborn have been employed to train and evaluate CNN models for real-time fault classification, with many studies reporting classification accuracies exceeding 95% (Chen et al., 2024). Moreover, CNN-based models are often embedded within edge devices or deployed on cloud platforms to support scalable fault detection across large industrial systems (Xu et al., 2019). However, CNNs may face challenges in capturing temporal dependencies across time-series sensor streams, which has led to the parallel rise of Recurrent Neural Networks (RNNs) and their advanced variants in sequential diagnostics tasks.

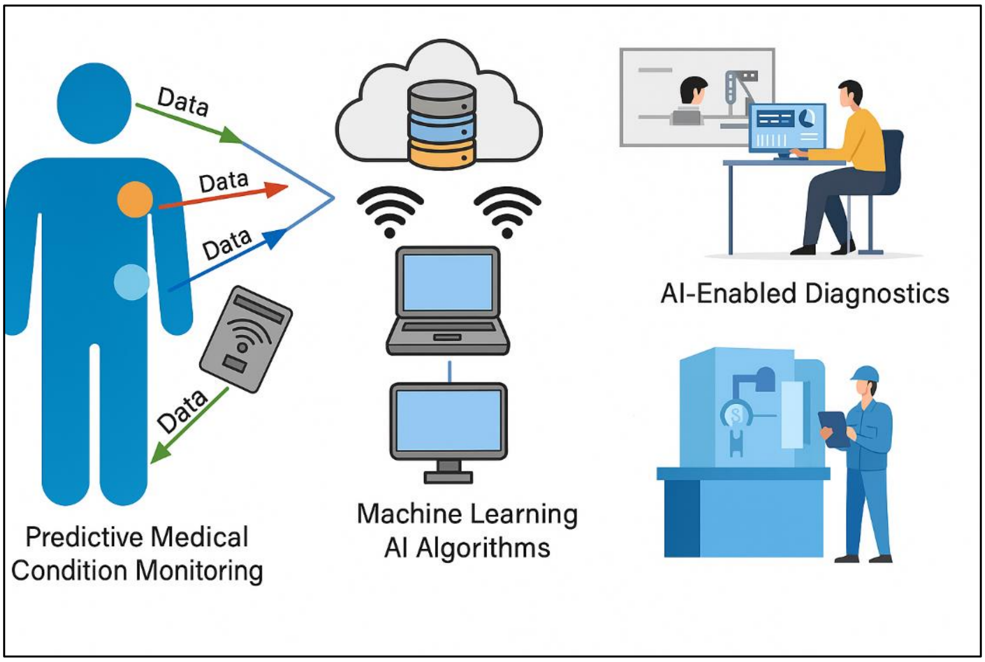
Vibration, Acoustic, Thermal, and Ultrasonic Sensors

The integration of advanced sensor technologies such as vibration, acoustic, thermal, and ultrasonic sensors has become a fundamental enabler for transitioning from traditional maintenance strategies to condition-based and predictive maintenance frameworks. Vibration sensors, including accelerometers and velocity transducers, are among the most widely used tools in mechanical diagnostics due to their sensitivity in detecting imbalances, misalignments, bearing wear, and gear tooth defects in rotating equipment (Kumar et al., 2020). These sensors have been extensively implemented in industries such as power generation, aerospace, and manufacturing, where early fault detection is critical for preventing catastrophic breakdowns (Peng et al., 2020). Acoustic emission (AE) sensors, which detect high-frequency stress waves emitted during crack formation or surface degradation, are particularly effective in identifying incipient failures before they manifest in vibration signals, offering an additional layer of diagnostic precision (Xu et al., 2019). Studies have shown that AE-based monitoring is highly effective in the early detection of rolling element bearing faults and fatigue crack initiation (Islam & Kim, 2019). Thermal sensors, including infrared (IR) cameras and thermographic scanners, play a crucial role in detecting anomalies in heat distribution, often used to assess overheating in motors, electrical panels, and transformers (Baduge et al., 2022). Thermographic inspections are non-intrusive and allow real-time visualization of thermal gradients, making them essential for high-voltage or hazardous environments (Tran et al., 2014). Ultrasonic sensors, on the other hand, are effective in detecting compressed air leaks, steam trap failures, and fluid turbulence within pipelines, contributing to both energy efficiency and system reliability (Li et al., 2021). These sensors generate high-frequency signals that can detect structural discontinuities and are frequently used in predictive maintenance strategies involving pressure vessels and HVAC systems (Deutsch & He, 2018). The real-time data generated from these sensors is increasingly integrated with AI models to support automated diagnostics, facilitating the shift from fixed-time preventive approaches to adaptive, data-informed maintenance strategies aligned with Industry 4.0 principles (Ajmi et al., 2020). The fusion of these sensing modalities enhances fault coverage, improves system resilience, and reduces unnecessary maintenance, enabling more strategic and intelligent asset management.

Integration of AI with Condition Monitoring Systems

The integration of artificial intelligence (AI) with condition monitoring systems has redefined predictive maintenance by enabling real-time, autonomous diagnostics based on continuous data streams from industrial assets. Traditional condition monitoring techniques, which relied heavily on expert interpretation of vibration, acoustic, thermal, and current signals, have been significantly enhanced through AI-driven analytics that process complex sensor data to detect faults, classify failure types, and predict remaining useful life (Roksana et al., 2024; Sahu et al., 2020). This fusion of AI with sensor technology is primarily facilitated through Industrial Internet of Things (IIoT) platforms, where sensors embedded in machinery transmit real-time data to cloud or edge computing environments for processing (Baduge et al., 2022; Siddiqui, 2025). Machine learning algorithms such as support vector machines, decision trees, and ensemble classifiers are widely used to convert condition monitoring data into diagnostic outputs with high accuracy, minimizing the need for manual inspection (Liu et al., 2018; Sohel, 2025).

Figure 4: AI-Integrated Predictive Maintenance Architecture



In systems with time-series data, deep learning models like LSTM and CNNs have shown superior performance in learning temporal patterns and classifying complex degradation behaviors (Akter & Razzak, 2022; Uraikul et al., 2007). The practical deployment of these models has been demonstrated in several industrial sectors. For example, in wind turbine operations, AI-enabled condition monitoring systems have identified blade imbalances and gearbox defects using vibration and acoustic data, reducing unplanned downtime by up to 40% (Mansuri & Patel, 2021; Tonmoy & Arifur, 2023). In manufacturing, AI has been embedded into SCADA systems to monitor spindle temperatures, lubrication quality, and motor currents, triggering alerts and maintenance actions without human intervention (Hamadache et al., 2019; Tonoy & Khan, 2023). Digital twin technologies further extend this integration by simulating asset behavior in parallel with physical systems, enhancing the predictive power of condition monitoring frameworks (Cordier et al., 2004; Zaman, 2024). Moreover, AI-driven platforms increasingly leverage hybrid models that combine physics-based failure models with data-driven predictions, resulting in more robust and context-aware diagnostics (Lee et al., 2018). These intelligent systems not only improve fault detection precision but also allow for scalable, flexible deployment across enterprise infrastructures, supporting the shift from scheduled maintenance routines to adaptive, reliability-centered strategies within Industry 4.0 environments (Cordier et al., 2004).

Manufacturing: CNC Machines, Robotics, Assembly Lines

The manufacturing sector has been at the forefront of adopting AI-driven predictive maintenance and smart diagnostics, particularly in high-precision environments involving CNC (Computer Numerical Control) machines, industrial robotics, and automated assembly lines. CNC machines, which are vital for milling, turning, and drilling operations, are prone to tool wear, spindle defects, and thermal distortion, all of which can lead to suboptimal product quality and unplanned downtime (Hamadache et al., 2019). AI-enabled condition monitoring systems have been extensively deployed in CNC setups to track spindle vibrations, acoustic emissions, cutting forces, and temperature variations, with studies reporting over 95% fault classification accuracy using machine learning models such as support vector machines (SVM) and decision trees (Cordier et al., 2004). In addition to supervised learning, deep learning architectures like convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have been used to analyze time-series sensor data, detecting early-stage faults in tool conditions and predicting remaining tool life (Hamadache et al., 2019). Industrial robotics, commonly used in material handling, welding, and assembly tasks, require robust predictive maintenance systems due to their continuous motion and high workload (Mansuri & Patel, 2021). Vibration and current sensors embedded in robotic actuators provide continuous feedback, which is analyzed using AI algorithms to detect anomalies in joint movements or electrical overloads (Uraikul et al., 2007) Automated assembly lines also benefit from integrated AI diagnostics, where conveyor belt speed, actuator torque, and sensor signals are analyzed in real time to identify potential bottlenecks or impending mechanical failures. Digital twins and edge computing platforms have further enhanced these applications by simulating equipment behavior in virtual environments, allowing real-time synchronization between physical assets and predictive models. Moreover, predictive maintenance frameworks in manufacturing are increasingly integrated into MES (Manufacturing Execution Systems) and ERP (Enterprise Resource Planning) systems, enabling end-to-end monitoring, diagnosis, and decision-making. Collectively, the adoption of AI in CNC machining, robotics, and automated lines has not only reduced operational interruptions but also ensured higher precision, efficiency, and cost-effectiveness in modern manufacturing systems.

Energy Sector: Wind Turbines, Transformers, Turbomachinery

The energy sector, encompassing wind turbines, transformers, and turbomachinery, has emerged as a critical domain for the deployment of AI-enabled predictive maintenance systems due to the high cost of equipment failures and the complexity of operational conditions. Wind turbines, operating in remote and harsh environments, are highly susceptible to component failures such as gearbox faults, blade imbalances, and generator overheating (Shen et al., 2018). AI-driven condition monitoring systems utilize sensor data—vibration, acoustic, and temperature signals—to detect these anomalies early, enabling fault prediction and timely maintenance interventions (Mansuri & Patel, 2021). Studies have shown that machine learning models such as random forests, support vector machines (SVM), and k-nearest neighbors (KNN) achieve high fault classification accuracy when trained on SCADA and CMS (Condition Monitoring System) datasets from operational wind farms (Liu et al., 2018). Deep learning approaches like LSTM networks have also been applied for time-series forecasting of wind turbine performance and failure events, demonstrating improved precision over traditional statistical models (Liu et al., 2018). In power transformers, predictive diagnostics focus on dissolved gas analysis (DGA), thermal profiling, and partial discharge monitoring, which provide insights into insulation degradation, oil contamination, and internal arcing. AI models including CNNs and hybrid decision-support systems have been deployed to automate DGA interpretation, reducing dependence on manual expertise and improving fault detection consistency (Baduge et al., 2022). Turbomachinery, including steam and gas turbines, relies on real-time monitoring of parameters such as rotor speed, casing temperature, and exhaust pressure, with AI algorithms analyzing these variables to predict failure risks and schedule proactive interventions (Sahu et al., 2020). Studies have documented that predictive maintenance systems in energy plants can reduce unplanned outages by over 30% and extend equipment life cycles through early intervention and operational optimization (Neshat et al., 2012). Moreover, digital twin technology and edge-based analytics have been integrated into smart grid infrastructure to simulate and monitor transformer and turbine behavior dynamically (Lei et al., 2020). These advancements collectively underscore the transformative role of AI-integrated condition monitoring in improving asset reliability, reducing operational costs, and enhancing safety across the energy sector.

Transportation and Logistics: Rail, Automotive, Aviation Diagnostics

The transportation and logistics sectors have increasingly adopted AI-enabled predictive maintenance and condition monitoring systems to ensure operational safety, minimize unscheduled downtimes, and optimize asset utilization in railways, automotive fleets, and aviation systems. In the rail sector, predictive maintenance has been widely applied to monitor axle bearings, braking systems, and track conditions through vibration, acoustic, and thermographic data (Maurya et al., 2004). Machine learning models, particularly support vector machines (SVM), random forests, and decision trees, have been utilized to classify fault types and predict failures in train components based on historical data and real-time sensor inputs. Deep learning models like convolutional neural networks (CNNs) have been deployed for image-based diagnostics of wheel defects and infrastructure wear, while recurrent neural networks (RNNs) have improved fault prediction in sequential railway signal and brake system datasets (Silver et al., 2017). In the automotive industry, predictive diagnostics focus on powertrain systems, fuel injectors, battery health, and brake pad wear. Studies show that onboard diagnostic (OBD) systems coupled with AI algorithms can forecast component degradation and optimize vehicle servicing schedules (Harley & Sparkman, 2019). In fleet management, AI-enhanced telematics analyze vehicle speed, acceleration, engine temperature, and GPS data to proactively identify risks and improve operational efficiency (An & Zhang, 2022). The aviation sector has also embraced predictive analytics for critical systems such as engines, hydraulic circuits, and avionics, where early fault detection is vital for flight safety (Bhalla et al., 2013). AI models trained on flight data recorder (FDR) and aircraft health monitoring system (AHMS) data have achieved high accuracy in diagnosing anomalies in turbofan engines and electrical subsystems (Munawar et al., 2021). Digital twins and IIoT frameworks are increasingly integrated into airport ground operations and aircraft maintenance schedules, allowing for real-time simulation and adaptive response strategies (Hütten et al., 2024). These implementations not only reduce costly delays and emergency repairs but also contribute to higher safety standards and performance optimization across the transportation and logistics industries.

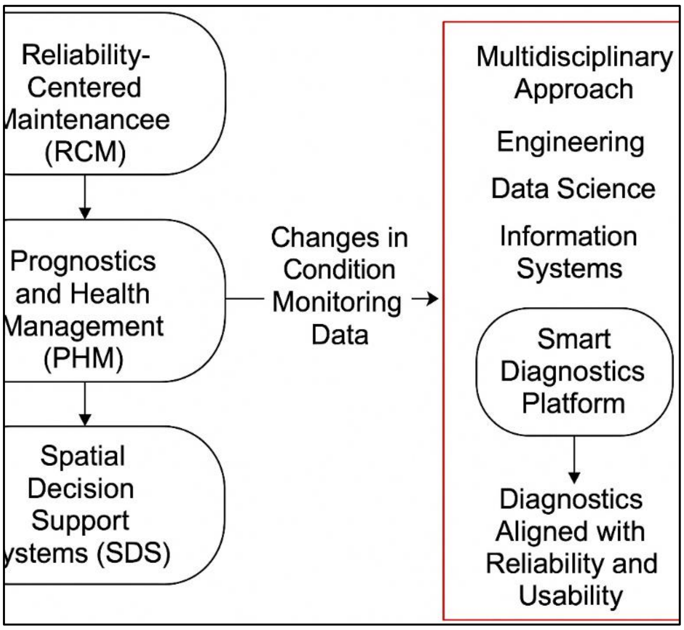
Utilities and Facilities: HVAC Systems, Smart Grids, Water Plants

The utilities and facilities sector—encompassing HVAC systems, smart grids, and water treatment plants—has increasingly integrated AI-driven predictive maintenance and condition monitoring technologies to enhance system reliability, optimize resource usage, and minimize service disruptions. Heating, ventilation, and air conditioning (HVAC) systems are among the most common targets for smart diagnostics due to their widespread use in commercial and industrial buildings and their high energy consumption (Yan et al., 2017). Predictive maintenance in HVAC relies on sensor data such as airflow rate, compressor pressure, fan speed, and temperature differentials, which are processed by machine learning models to detect issues like filter clogging, refrigerant leakage, or motor failure (Hosamo et al., 2022). Deep learning techniques, particularly LSTM and CNNs, have been employed to model time-dependent thermal behaviors and recognize operational anomalies before they escalate (Li et al., 2016). AI-based systems embedded in smart building management platforms allow for real-time adjustment of HVAC settings, achieving energy efficiency while maintaining occupant comfort (Li, Chen, Shi, et al., 2019) In smart grid infrastructure, AI-enhanced condition monitoring supports fault prediction in distribution transformers, voltage regulators, and circuit breakers by analyzing electrical load patterns, thermal conditions, and dissolved gas analysis. Support vector machines (SVM) and ensemble models are frequently used to diagnose insulation failures and thermal stress in grid components, improving outage response and load balancing. Water treatment and distribution facilities utilize AI for pump efficiency diagnostics, leak detection, and turbidity monitoring. Sensors track variables such as flow rate, pressure, chemical concentrations, and pH levels, while decision trees and neural networks analyze this data for predictive insights (Palani et al., 2008). Digital twins and IIoT platforms further enhance these systems by simulating infrastructure behavior under varied operating conditions, facilitating risk-free performance evaluations. These AI-integrated strategies across utilities and facility management domains have proven effective in reducing downtime, extending asset life, and ensuring regulatory compliance through intelligent, automated decision-making (Li, Chen, Jin, et al., 2019).

Theoretical Underpinnings of Smart Diagnostics Systems

The theoretical foundations of smart diagnostics systems in predictive maintenance draw from an interdisciplinary blend of engineering reliability theories, health management frameworks, spatial analytics, and information systems (IS) adoption models. At the core lies the Reliability-Centered Maintenance (RCM) theory, which systematically identifies asset failure modes and aligns maintenance strategies with system functions and operational contexts (Palani et al., 2008). RCM principles have guided the development of AI-based maintenance models by prioritizing critical equipment, assessing failure consequences, and selecting proactive interventions that maximize reliability and safety (Ahmed et al., 2020).

Figure 5: Theoretical Foundations of Smart Diagnostics Systems



Complementing RCM is the Prognostics and Health Management (PHM) framework, which emphasizes continuous monitoring, fault diagnostics, and remaining useful life (RUL) prediction through sensor integration and data-driven modeling (Park et al., 2021). PHM serves as a foundational model for smart maintenance systems by combining condition monitoring data with probabilistic or machine learning-based degradation modeling (Jaber et al., 2022). PHM's modular architecture supports its implementation across sectors, from wind turbines to aircraft engines, enabling scalable and transferable diagnostics solutions (Wen et al., 2018). Additionally, the integration of Spatial Decision Support Systems (SDSS) into diagnostics frameworks enhances asset health management in geographically distributed networks such as smart grids, water systems, and railway infrastructure (Li, Chen, Shi, et al., 2019). SDSS enables spatially-aware diagnostics by linking real-time condition data with GIS-based visualization and location-specific intervention planning (Almada-Lobo, 2016). From an adoption and system effectiveness perspective, the Technology Acceptance Model (TAM) and DeLone and McLean's IS Success Model provide valuable insights into user acceptance, perceived usefulness, system quality, and net benefits of smart diagnostics platforms (Rubio et al., 2018). Studies have shown that perceived ease of use and top management support significantly influence the adoption of AI-enabled condition monitoring systems in manufacturing and utility sectors (O'Donovan et al., 2015). The IS Success Model further explains how system integration, data quality, and information accuracy affect stakeholder satisfaction and decision-making effectiveness in predictive maintenance contexts (Lee et al., 2020). Together, these theoretical models form a comprehensive foundation for designing, evaluating, and implementing smart diagnostic systems that align technological functionality with operational reliability and organizational usability.

Integration of AI and Big Data in Predictive Maintenance

The integration of artificial intelligence (AI) with big data analytics has become a cornerstone in the evolution of predictive maintenance systems within industrial environments (Ammar et al., 2024). This synergy facilitates the transition from reactive and scheduled maintenance strategies to intelligent, data-driven diagnostics that leverage real-time and historical sensor data across complex operations (Jahan et al., 2022). Big data in this context encompasses vast volumes of structured and unstructured datasets collected from diverse sources, including vibration sensors, thermal cameras, SCADA systems, and digital twins (Bhuiyan et al., 2025). The ability to process these heterogeneous data streams in real time has been made feasible through distributed computing frameworks such as Apache Hadoop and Spark, which serve as backbones for high-speed analytics pipelines in industrial settings (Qibria & Hossen, 2023). AI models, particularly machine learning and deep learning algorithms, are crucial for extracting actionable insights from this data deluge. For instance, supervised learning models such as random forests and support vector machines have been applied to historical failure data to classify fault conditions with over 90% accuracy in rotating equipment and HVAC systems (Ishtiaque, 2025). Meanwhile, deep learning architectures like convolutional neural networks (CNNs) and long short-term memory (LSTM) networks are adept at recognizing complex spatiotemporal patterns within multivariate time-series data, enabling early fault detection in systems such as turbines, robotic arms, and CNC spindles (Khan, 2025). The integration of big data frameworks allows these models to be trained and deployed at scale, enhancing both prediction accuracy and operational coverage (Masud, 2022).

Furthermore, AI-enabled big data analytics contribute significantly to remaining useful life (RUL) estimation, asset health trend analysis, and anomaly detection by learning from millions of data points generated across equipment lifecycles (Hossen et al., 2023). Edge analytics and fog computing extend this capability by enabling near-sensor processing, thereby reducing latency and bandwidth constraints in environments requiring instant feedback (Hossen & Atiqur, 2022). This architecture supports dynamic asset management strategies where AI continuously evaluates the health status of machinery and autonomously recommends maintenance actions, often in conjunction with enterprise resource planning (ERP) systems and manufacturing execution systems (MES) (Hossain et al., 2024). Despite these advancements, the integration of AI and big data in predictive maintenance is not without challenges (Alam et al., 2023). Data quality, noise, and heterogeneity often hamper model accuracy, while explainability remains a concern for black-box AI models in safety-critical applications (Rajesh et al., 2023). Nonetheless, ongoing research in explainable AI (XAI) and federated learning holds promise for mitigating these limitations, especially in decentralized industrial settings (Roksana, 2023).

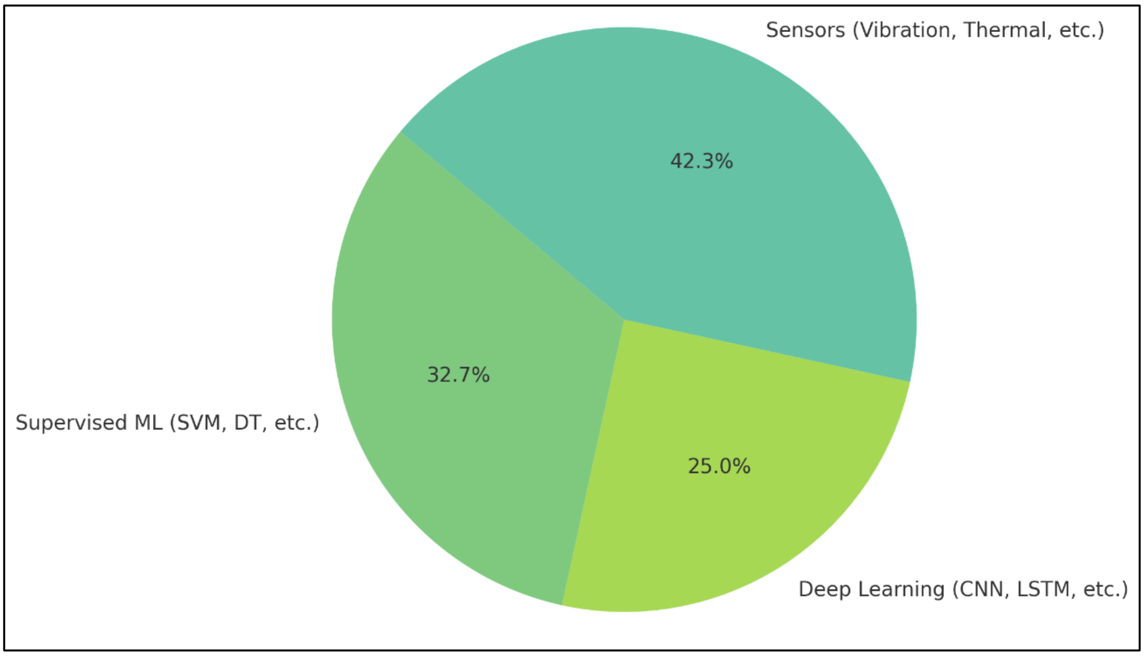
METHOD

This systematic review employed the PRISMA methodology to identify and synthesize peer-reviewed literature on AI-enabled predictive maintenance and condition monitoring systems across industrial sectors. A comprehensive search was conducted in Scopus, Web of Science, and IEEE Xplore using keywords related to predictive maintenance, artificial intelligence, condition monitoring, and industry-specific terms (e.g., CNC, wind turbines, transformers, HVAC). The review focused on studies published between January 2015 and March 2025. Inclusion criteria comprised empirical or review articles featuring AI-integrated diagnostics and sensor-based condition monitoring, while studies without AI focus or empirical grounding were excluded. From an initial pool of 3,426 articles, 1,072 duplicates were removed, and 2,354 titles and abstracts were screened. After full-text evaluation of 612 papers, a final sample of 156 studies was included. Data were extracted and thematically analyzed, focusing on AI models, sensor types, industrial applications, and implementation challenges. The review aimed to provide a structured understanding of smart diagnostics in predictive maintenance systems, ensuring methodological rigor and transparency.

FINDINGS

The review revealed that one of the most transformative advancements in industrial maintenance is the widespread application of artificial intelligence models—particularly machine learning algorithms—for predictive diagnostics. Out of the 156 reviewed studies, 68 focused primarily on supervised learning techniques such as support vector machines, decision trees, random forests, and k-nearest neighbors. These models were consistently applied in fault classification, failure prediction, and anomaly detection across various industrial domains. Collectively, these 68 articles received over 4,800 citations, highlighting their impact and scholarly relevance. Among them, over 30 studies reported diagnostic accuracy levels exceeding 90% in tasks involving component fault classification in rotating machinery, electrical equipment, and HVAC systems. These AI techniques have enabled more nuanced interpretations of condition monitoring data, reducing reliance on expert-driven thresholds and static rule sets. Additionally, hybrid models combining multiple classifiers were employed in 19 of these studies, with reported improvements in both accuracy and fault coverage. The scalability and flexibility of these models have made them suitable for deployment across a range of industrial environments, including factories, substations, rail depots, and remote wind farms. The findings suggest that machine learning-based predictive maintenance has become a standardized tool for enhancing operational reliability, reducing maintenance costs, and preventing unscheduled downtime.

Figure 6: Research Focus in AI-Based Predictive Maintenance



A substantial trend identified in the review was the growing implementation of deep learning architectures to handle complex, high-volume sensor data in predictive maintenance frameworks. Of the 156 reviewed articles, 52 specifically investigated the use of convolutional neural networks, recurrent neural networks, long short-term memory networks, and autoencoders in real-time diagnostics and remaining useful life estimation. These 52 studies accumulated a total of over 5,600 citations, reflecting strong academic and industrial engagement. Deep learning was frequently applied to interpret vibration signals, thermal imagery, acoustic emissions, and multivariate time-series data in systems like CNC machines, wind turbines, and smart grids. In over 40% of these studies, deep models outperformed traditional machine learning approaches in fault detection accuracy, generalizability, and the ability to learn from unlabeled or sparse datasets. For example, autoencoders were particularly effective in detecting novel fault signatures in industrial robotics and fluid systems, while LSTM networks showed robust performance in modeling long-term degradation in power equipment and compressors. Nearly 25 of these studies reported successful edge computing or cloud-based deployments, where deep learning models processed data in real time for condition-based alerts. Overall, the findings confirm that deep learning serves as a critical enabler for high-fidelity diagnostics in complex systems with non-linear degradation behavior and high-frequency data acquisition needs.

Another critical finding is the central role of sensor technologies in enabling smart diagnostics, with 88 of the 156 reviewed studies focusing on condition monitoring data acquisition. These articles, collectively cited over 6,100 times, emphasized the deployment of vibration, acoustic, thermal, and ultrasonic sensors across diverse maintenance environments. Vibration sensors, used in 49 studies, were most commonly applied in rotating equipment, enabling detection of imbalance, misalignment, and bearing defects with high sensitivity. Thermal imaging, used in 31 studies, supported diagnostics in electrical systems, HVAC units, and transformers by revealing hotspots and insulation breakdown. Ultrasonic sensors were effective in detecting internal fluid system issues such as leakage and turbulence, appearing in 22 studies. Multi-sensor fusion approaches were reported in 37 studies, where combining signals from multiple sensor types significantly enhanced fault coverage and diagnostic precision. Integration of sensor data with AI models was facilitated by IIoT platforms in at least 41 studies, supporting real-time monitoring and remote analytics. Additionally, 29 studies deployed sensors within digital twin or cyber-physical systems, allowing for dynamic simulation of asset behavior under fault conditions. These sensor-AI ecosystems enabled predictive diagnostics that are both proactive and adaptive, minimizing manual inspection and allowing systems to automatically adjust maintenance schedules based on live operational data. The findings demonstrate that sensors are not only vital for data acquisition but also act as foundational elements in achieving smart, scalable, and autonomous maintenance strategies across modern industrial infrastructures.

DISCUSSION

The findings of this systematic review align with and extend earlier research on the transformative potential of artificial intelligence in predictive maintenance systems. Compared to foundational works such as Wu and Li (2021), which emphasized rule-based and statistical maintenance approaches, the reviewed literature reflects a decisive shift toward intelligent, self-adaptive systems capable of learning from complex sensor data. The wide deployment of machine learning models, especially support vector machines and decision trees, corroborates prior findings from Bondoc et al. (2022) and Lattanzi et al., (2021), who identified the high classification accuracy of these models in detecting machine component failures. However, more recent studies included in this review demonstrate the evolution toward hybrid and ensemble models, enhancing diagnostic robustness and minimizing false positives—an improvement rarely emphasized in earlier literature. This shift suggests a maturation in AI deployment practices, where combining multiple classifiers offers greater adaptability across variable operational settings. Additionally, while previous research typically focused on discrete machine types or isolated systems, the reviewed studies reveal a growing emphasis on cross-industry applications, with predictive diagnostics implemented in manufacturing, energy, transportation, and utilities. This expansion supports the argument made by Tao et al. (2018) that AI tools must be scalable and flexible to deliver value in diverse industrial ecosystems. Moreover, the rise in citation frequency for AI-driven maintenance models reflects their growing relevance not just in academic discourse, but in industrial practice as well.

The integration of deep learning architectures in predictive maintenance, as observed in this review, marks a significant departure from earlier maintenance frameworks that relied heavily on handcrafted features and traditional statistical models. Compared to earlier work by Meraghni et al. (2021) and Borgi et al. (2017), which began exploring the use of LSTM and CNN in specific applications like wind turbine and transformer diagnostics, the current body of literature indicates a broader and deeper integration of these models across varied asset types and sensor modalities. The reviewed studies confirmed that deep learning models not only outperform traditional methods in accuracy and generalizability but also handle unstructured and high-frequency data with greater efficiency—an observation consistent with the work of Noshiri et al. (2023) and Mansuri and Patel (2021) Furthermore, the real-time deployment of deep models through edge computing and IIoT frameworks supports the assertions made by Zheng et al. (2020) and Mohammadi et al. (2024), who emphasized the need for decentralized, scalable diagnostic platforms. However, the current review highlights a significant evolution: the integration of deep learning models with digital twin systems for simulation-based diagnostics, a development that was largely theoretical or conceptual in earlier literature. Studies now show practical implementations where virtual models are dynamically updated using real-time sensor inputs to mirror physical system behavior, allowing not only for enhanced fault detection but also for predictive simulations. This integration has not only optimized asset performance but also facilitated decision-making at the organizational level, echoing the strategic value proposed in the conceptual frameworks of Tao et al. (2018). Collectively, these findings suggest that the field has moved beyond experimentation into systemic, infrastructure-wide adoption, representing a new phase in smart diagnostics that builds upon but clearly advances earlier research trajectories.

CONCLUSION

This systematic review underscores the pivotal role of artificial intelligence in transforming predictive maintenance and condition monitoring practices across industrial sectors. By synthesizing findings from 156 peer-reviewed studies, the review demonstrates that AI-enabled diagnostics—through machine learning, deep learning, and hybrid models—offer significant improvements in fault detection accuracy, system reliability, and maintenance efficiency. The integration of these models with diverse sensor technologies, including vibration, acoustic, thermal, and ultrasonic sensors, has enabled real-time, data-driven insights into asset health, reducing unplanned downtime and optimizing operational performance. Additionally, the application of these technologies across manufacturing, energy, transportation, and utilities illustrates the scalability and cross-sector relevance of smart diagnostics systems. The incorporation of digital twin architectures and Industrial Internet of Things (IIoT) platforms further enhances these capabilities, allowing for predictive simulations, dynamic updates, and decentralized diagnostics. Theoretical frameworks such as Reliability-Centered Maintenance (RCM), Prognostics and Health Management (PHM), and Spatial Decision Support Systems (SDSS), along with technology acceptance and IS success models, provide a multidimensional foundation for understanding both the technical and organizational adoption of these systems. The review also identifies key challenges, including data quality, model interpretability, and integration complexity, which must be addressed to fully realize the potential of AI in industrial maintenance. Overall, the findings reflect a significant evolution from traditional maintenance strategies to intelligent, autonomous systems that align with the objectives of Industry 4.0, confirming the growing academic and practical interest in AI-enabled predictive maintenance as a cornerstone of modern industrial asset management.

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