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PREDICTIVE MAINTENANCE IN POWER TRANSFORMERS: A SYSTEMATIC REVIEW OF AI AND IOT APPLICATIONS

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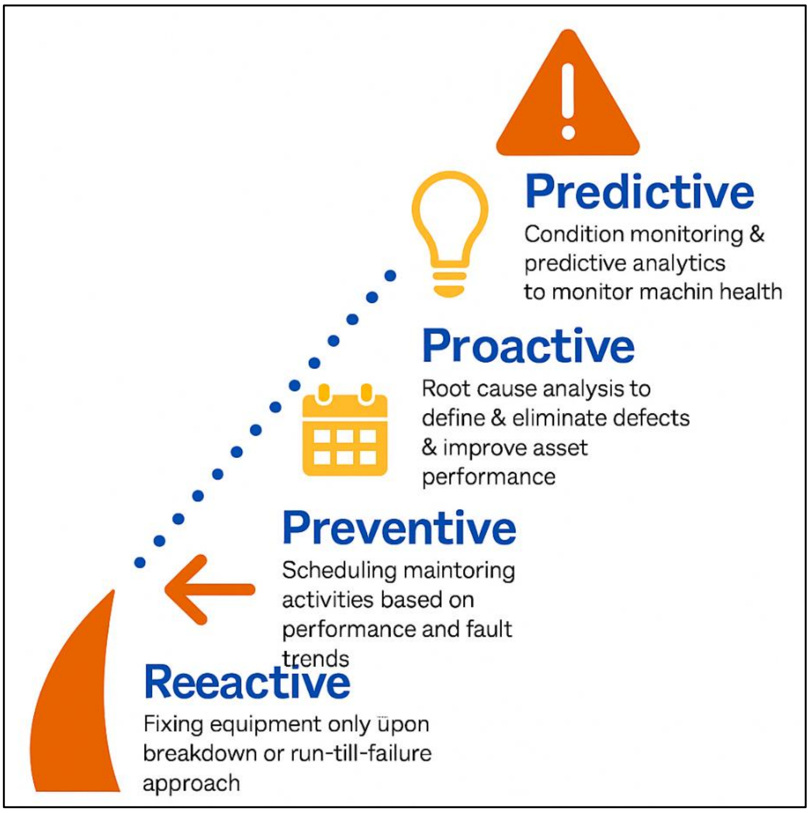
Abstract
Power transformers are critical assets in electrical power systems, and their failure can result in costly downtime and catastrophic grid disruptions. This systematic review investigates the emerging role of Artificial Intelligence (AI) and Internet of Things (IoT) technologies in enabling predictive maintenance (PdM) of power transformers. Drawing upon 126 peer-reviewed articles published between 2015 and 2024, this review categorizes and synthesizes state-of-the-art techniques involving sensor integration, real-time condition monitoring, data fusion, machine learning (ML), deep learning, and digital twin frameworks. The analysis reveals a growing trend toward hybrid PdM models that leverage transformer health indices, vibration and thermal imaging, dissolved gas analysis (DGA), and partial discharge (PD) data. Neural networks, support vector machines, decision trees, and ensemble methods dominate the AI approaches, while IoT-based sensor networks and cloud-edge computing architectures underpin the system infrastructures. Key challenges identified include data heterogeneity, cybersecurity vulnerabilities, high initial costs, and lack of standardization in deployment practices. This review concludes that integrating AI and IoT in transformer maintenance not only enhances fault detection and failure prediction but also supports asset lifecycle optimization and grid resilience. The findings contribute to academic research and industrial applications by providing a consolidated framework for future development, standardization, and policy formulation in smart grid systems.

Keywords
Predictive Maintenance, Power Transformers, Artificial Intelligence (AI), Internet of Things (IoT), Machine Learning, Condition Monitoring, Digital Twin, Smart Grid.

INTRODUCTION

Predictive maintenance (PdM) refers to the strategy of monitoring the actual condition of equipment to predict when maintenance should be performed, thereby minimizing unscheduled downtime and maximizing operational efficiency (Delmas et al., 2018). In contrast to reactive or time-based maintenance, PdM relies on real-time data, historical records, and analytical models to identify potential failures before they occur (Sánchez & Cortés, 2021). Within the power sector, power transformers are essential components in the transmission and distribution network, responsible for voltage regulation and energy transfer across vast distances (Divya et al., 2022). Failures in these transformers can result in blackouts, economic losses, and system instability (Zhao et al., 2022). Traditional condition-based maintenance strategies, which utilize diagnostic tests such as dissolved gas analysis (DGA) and partial discharge (PD) measurement, have proven useful but often fall short in providing timely and accurate predictions for incipient faults (Babu et al., 2022). Consequently, there is increasing emphasis on data-driven PdM strategies supported by Artificial Intelligence (AI) and Internet of Things (IoT) technologies, which can offer continuous monitoring, pattern recognition, and advanced anomaly detection capabilities (Namuduri et al., 2020)

Figure 1: Transformer Maintenance Strategies: From Reactive to Predictive



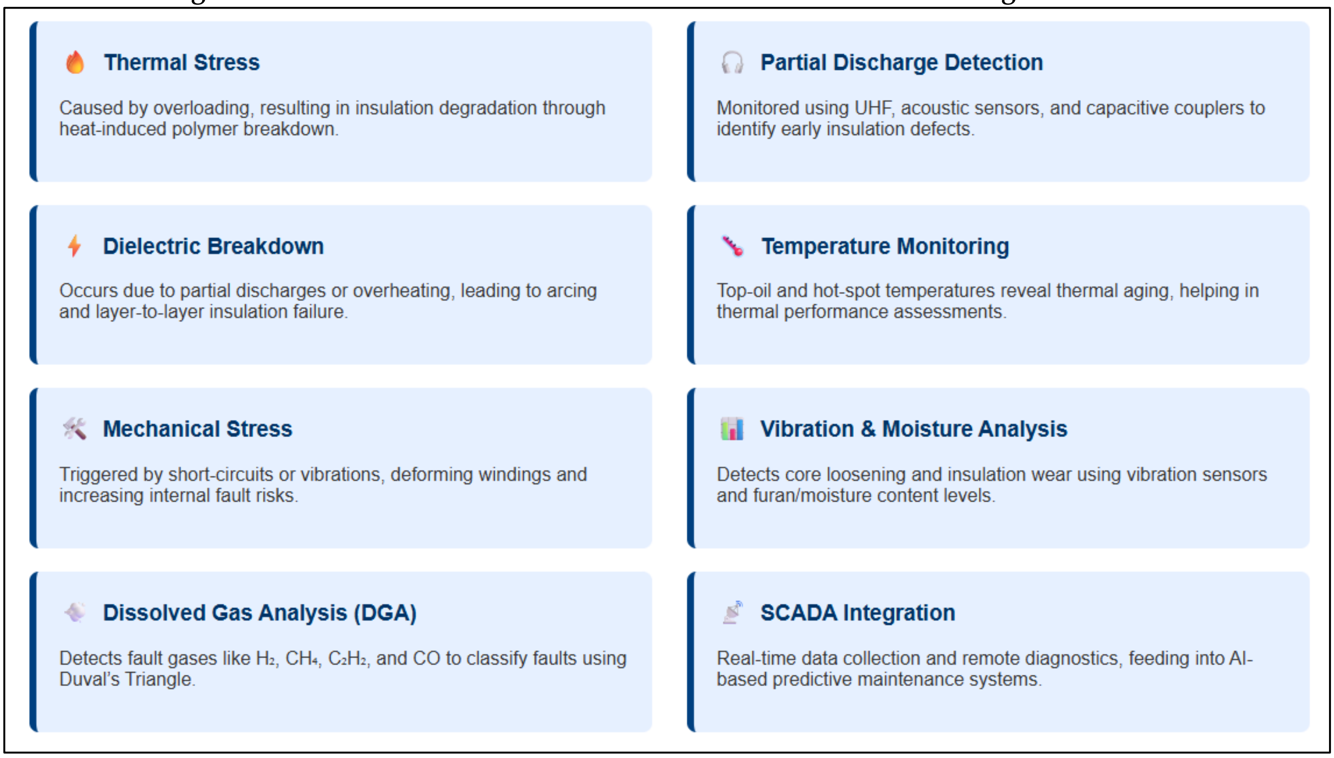
The integration of AI and IoT into transformer maintenance enables a multidimensional understanding of asset health by synthesizing large volumes of heterogeneous data from temperature sensors, acoustic emission devices, gas chromatographs, and vibration analyzers (Allahloh et al., 2023). IoT facilitates real-time data acquisition through interconnected devices and edge/cloud-based architectures (Mourtzis et al., 2023), while AI techniques, such as artificial neural networks (ANN), support vector machines (SVM), decision trees (DT), random forests (RF), and deep learning models, provide robust prediction and classification mechanisms (Liu et al., 2018). Several studies have demonstrated the superiority of these models in forecasting fault progression, transformer aging, insulation degradation, and thermal stress (De Bernardi et al., 2024). For instance, ANNs trained on historical DGA datasets have shown high accuracy in identifying fault types and severity levels (Gilles et al., 2023). Similarly, ensemble methods have been employed to reduce the variance and bias in transformer failure prediction (Ouadah et al., 2022). These methodologies are further enhanced by digital twin models that replicate the operational behavior of transformers in virtual environments (Lakehal et al., 2018). By leveraging the synergies between AI and IoT, the power industry is increasingly adopting predictive diagnostics as a strategic approach to enhance transformer reliability and safety (Liu et al., 2022).

The objective of this systematic review is to critically examine and consolidate existing scholarly research on the application of Artificial Intelligence (AI) and Internet of Things (IoT) technologies in predictive maintenance (PdM) strategies for power transformers. This review aims to identify, categorize, and analyze the state-of-the-art models, algorithms, sensor systems, and data analytics frameworks that contribute to transformer condition monitoring, fault diagnosis, and failure prediction. The central purpose is to bridge fragmented insights across multidisciplinary studies and provide a structured understanding of how AI-driven methods—such as artificial neural networks (ANN), support vector machines (SVM), decision trees (DT), random forest (RF), k-nearest neighbors (KNN), and deep learning—are integrated with IoT infrastructures, including edge computing, wireless sensor networks, and cloud-based platforms, to enhance the reliability, safety, and longevity of transformer operations. Furthermore, the review aims to identify existing challenges—such as data interoperability, lack of standardization in IoT protocols, limitations in labeled datasets, and cybersecurity threats—that hinder the full-scale deployment of AI-IoT predictive frameworks in power utilities. By accomplishing these objectives, the review provides a comprehensive academic foundation for utility engineers, researchers, and policymakers to understand current capabilities, gaps, and deployment strategies in smart transformer maintenance ecosystems. Ultimately, the study contributes to a unified knowledge base that informs strategic decision-making in asset management and operational risk reduction in electrical power infrastructure.

Transformer Failure Mechanisms and Condition Monitoring Parameters

Power transformers are critical components in power systems, and their failure can result in major operational disruptions, safety hazards, and financial losses (Tang et al., 2014). These assets are vulnerable to a variety of internal and external stressors, including thermal overloading, dielectric breakdown, short-circuit stress, and mechanical fatigue, each of which contributes to insulation degradation and eventual failure (Zhang et al., 2021). Thermal stress, in particular, accelerates the aging of cellulose-based insulation, resulting in chemical decomposition and loss of dielectric strength. Dielectric failures, often stemming from localized overheating or partial discharges, compromise the insulation between winding layers and lead to arcing or breakdown events (Aliyu et al., 2024). Mechanical stresses, including those induced by short-circuit currents and transportation vibrations, can deform the windings and core, increasing the risk of internal faults.

Figure 2: Transformer Failure Mechanisms and Condition Monitoring Parameters



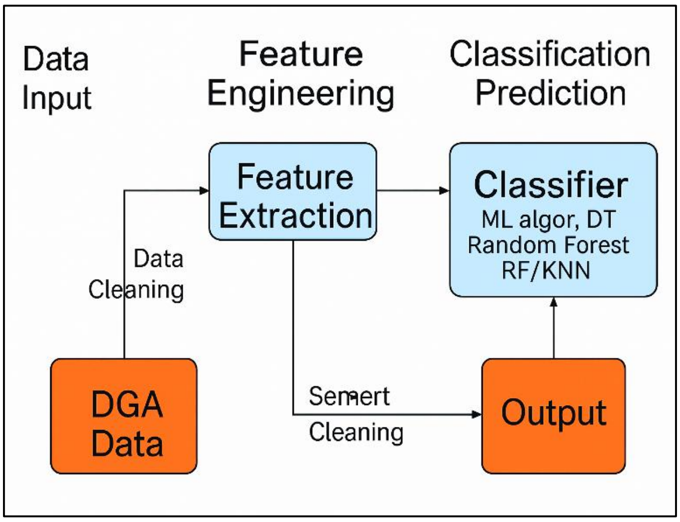
Among the diagnostic tools available, Dissolved Gas Analysis (DGA) has emerged as a principal method for identifying thermal and electrical anomalies (Gordon et al., 2020). By detecting the presence and ratio of gases such as hydrogen, methane, ethylene, acetylene, and carbon monoxide, DGA allows for the categorization of faults into thermal or electrical types. For example, elevated ethylene and acetylene levels typically indicate arcing or overheating, while increased hydrogen levels may point to partial discharges or corona activity (Aqueveque et al., 2021). These gas patterns are frequently used in conjunction with Duval's Triangle or other graphical tools to determine fault types with reasonable

accuracy and repeatability.
In parallel, other condition monitoring parameters and diagnostic techniques contribute to a more comprehensive assessment of transformer health (Rafezi & Hassani, 2023). Partial Discharge (PD) detection remains a vital tool for identifying early insulation deterioration, particularly in high-voltage equipment. PD activity is commonly captured using acoustic emission sensors, ultra-high frequency (UHF) sensors, or capacitive couplers, each capable of detecting subtle electromagnetic pulses generated by insulation voids or defects (Wang et al., 2017). Additionally, monitoring top-oil temperature and winding hot-spot temperature provides insights into the thermal performance and load-induced aging of the transformer. Elevated temperatures can accelerate polymer degradation, which in turn affects mechanical strength and dielectric reliability. Vibration analysis has been employed to detect anomalies associated with core loosening or winding displacement, particularly under dynamic load conditions. Moisture content in the insulation, furan concentration in oil, and historical load patterns are further indicators of long-term degradation and insulation life expectancy (Gunckel et al., 2025). Many of these parameters are collected and managed through Supervisory Control and Data Acquisition (SCADA) systems, which facilitate remote diagnostics, alarm generation, and integration with digital relays for fault localization (Roy et al., 2024). These systems also enable the development of AI-based predictive maintenance models, where historical and real-time data streams are analyzed to detect patterns that precede failure (Salem et al., 2023). When combined, these diverse indicators provide a multidimensional perspective on transformer condition, enabling utility operators to make informed decisions regarding maintenance prioritization and asset replacement strategies (Wahid et al., 2022).

AI Algorithms for Transformer Fault Detection and Diagnosis

Artificial Intelligence (AI) has become a pivotal force in transforming predictive maintenance frameworks for power transformers, moving beyond conventional threshold-based and rule-driven diagnostic techniques toward adaptive, data-centric models capable of handling nonlinear, high-dimensional fault characteristics (Ammar et al., 2024; Matzka, 2020). Among the most widely adopted AI methodologies are Machine Learning (ML) algorithms such as Support Vector Machines (SVM), Decision Trees (DT), Random Forest (RF), and K-Nearest Neighbors (KNN), which are predominantly employed for analyzing Dissolved Gas Analysis (DGA) data (Jahan et al., 2022). DGA remains a critical diagnostic tool, and AI models significantly enhance its interpretive power by classifying fault types with higher accuracy and faster computation (Bhuiyan et al., 2025; Cardoso & de Souza Ferreira, 2020). SVM models, known for their effectiveness in handling small-to-medium-sized datasets, have consistently demonstrated superior performance in multi-class classification problems involving gas ratio methods (Qibria & Hossen, 2023). In studies where gas signatures vary across arc faults, thermal faults, and partial discharges, SVMs have yielded accuracy rates exceeding 90% under cross-validation settings (Ishtiaque, 2025; Ucar et al., 2024). Likewise, Decision Trees and Random Forest models are praised for their transparency and ensemble robustness, respectively, with RF models often outperforming standalone classifiers due to their ability to reduce overfitting and handle high-dimensional inputs effectively (Bojarczuk et al., 2021; Khan, 2025).

Figure 3: AI-Driven Fault Diagnosis Framework Using DGA Data



Artificial Neural Networks (ANN), particularly those using feedforward and backpropagation learning architectures, have emerged as highly effective for fault prediction due to their nonlinear mapping capability and tolerance for noisy input data (Lee, 2023; Masud, 2022). These models have been trained on a wide array of transformer operating parameters—ranging from DGA signatures and thermal data to vibration and partial discharge signals—

enabling condition assessment across different degradation pathways (Hossen et al., 2023). In recent years, Deep Learning (DL) architectures have pushed the boundaries further by extracting hierarchical patterns from complex sensor datasets (Ferraro et al., 2022; Hossen & Atiqur, 2022). Convolutional Neural Networks (CNNs) are widely used for image-based diagnostics, such as thermal imaging and infrared scans of transformer surfaces, while Long Short-Term Memory (LSTM) networks are better suited for sequential data streams such as temperature or load histories (Arrieta et al., 2020; Hossain et al., 2024). These models excel in capturing temporal dependencies that simpler ML models might overlook. Ensemble techniques like XGBoost and AdaBoost, which combine multiple weak classifiers, have also gained popularity for their high diagnostic performance and resilience against data imbalance—a common challenge in transformer fault datasets (Alam et al., 2023; Youness & Aalah, 2023). Furthermore, hybrid models that blend AI algorithms with fuzzy logic systems provide enhanced decision-making under uncertainty, offering both interpretability and adaptive reasoning (Bordegoni & Ferrise, 2023; Rajesh et al., 2023). These hybrid approaches are particularly valuable in practical applications where fault signatures are ambiguous or influenced by multiple interacting variables. Increasingly, these AI algorithms are being embedded into edge computing platforms and online diagnostic tools, allowing for real-time transformer health monitoring with high sensitivity and reduced false alarm rates (Fera & Spandonidis, 2024; Roksana, 2023). Such capabilities enable utility operators to initiate timely maintenance interventions, optimize asset utilization, and extend the operational lifespan of power transformers.

IoT Architectures and Sensor-Based Monitoring Systems

The integration of Internet of Things (IoT) architectures into transformer maintenance ecosystems has markedly transformed traditional monitoring practices, offering substantial advancements in data precision, system responsiveness, and operational scalability (Roksana et al., 2024; Virat et al., 2022). IoT-enabled sensors—permanently embedded within transformer units—are now widely deployed to collect real-time measurements of key electrical, thermal, mechanical, and chemical indicators, including load current, winding and top-oil temperatures, ambient humidity, dissolved gas concentrations, vibration levels, and insulation moisture. These sensor arrays transmit high-resolution data using communication protocols such as Modbus, ZigBee, LoRaWAN, and MQTT, allowing seamless interoperability with local gateways and cloud-based storage and analytics platforms (Foukalas, 2020; Siddiqui, 2025). Wireless Sensor Networks (WSNs), which comprise spatially distributed sensor nodes, enable multi-point condition monitoring across entire substations or distributed grid zones, thereby offering a non-intrusive, scalable approach to asset surveillance (Cheng et al., 2020; Sohel, 2025). The recent adoption of edge computing further enhances these capabilities by processing data at or near the sensor node, significantly reducing latency, alleviating bandwidth limitations, and allowing for faster anomaly detection and autonomous fault response (De Luca et al., 2023; Akter & Razzak, 2022). These edge systems often utilize lightweight AI models to execute real-time diagnostics locally before transmitting alerts or aggregated insights to the cloud. IoT infrastructures are increasingly integrated with Supervisory Control and Data Acquisition (SCADA) systems and broader Industrial Internet of Things (IIoT) frameworks, enabling centralized dashboards, remote access, automated reporting, and condition-based maintenance scheduling (Baruah, 2021; Tonmoy & Arifur, 2023). However, emerging challenges such as sensor calibration drift, data synchronization errors, network congestion, and cybersecurity vulnerabilities—especially in open-access communication environments—pose persistent barriers to reliability and scalability (Dhanraj et al., 2020; Tonoy & Khan, 2023). Despite these limitations, the collective body of literature underscores the critical role of IoT in enabling continuous, high-fidelity monitoring that supports AI-driven predictive maintenance, ultimately enhancing transformer reliability, reducing maintenance costs, and extending asset life across interconnected power systems (Zaman, 2024).

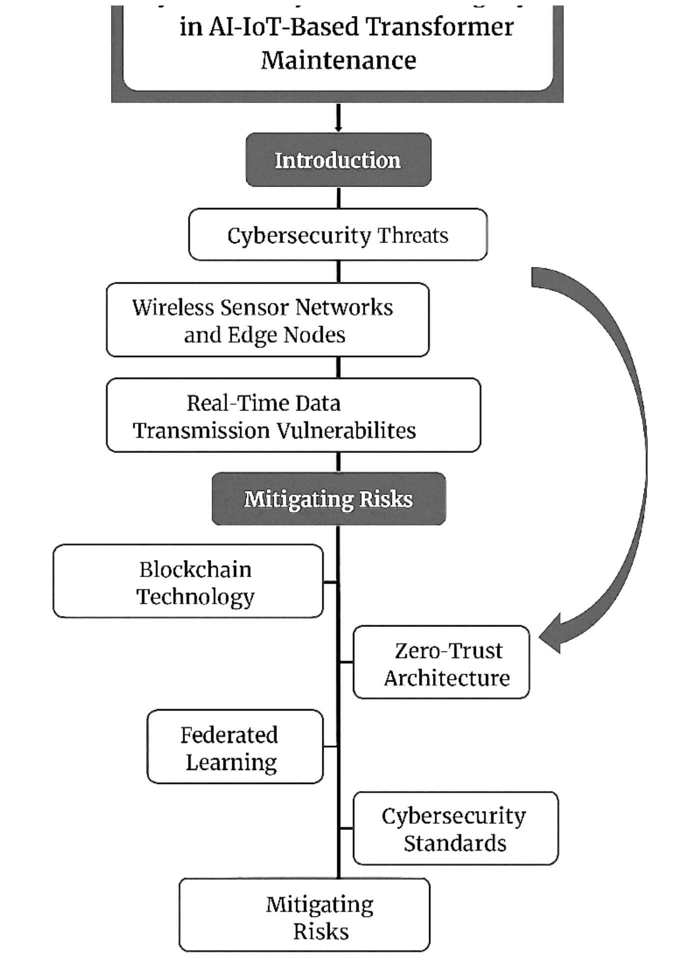
Hybrid Predictive Maintenance Models and Digital Twin Integration

Hybrid predictive maintenance models that integrate Artificial Intelligence (AI) and Internet of Things (IoT) technologies represent a sophisticated evolution in transformer asset management, enabling deeper insights, adaptive learning, and dynamic decision-making (Rojas et al., 2025). These integrated systems leverage the real-time data collection capabilities of IoT with the analytical and predictive power of AI to build a closed-loop maintenance architecture that continuously monitors, assesses, and forecasts transformer health. At the forefront of this paradigm is digital twin technology, which involves the creation of virtual counterparts of physical transformers that synchronize in real-time with operational data streams from embedded IoT sensors (Cancemi & Lo Frano, 2022). These digital replicas dynamically simulate the operational behavior of transformers under varying stress conditions, environmental factors, and historical usage profiles, enabling early anomaly detection and long-range prognostics (Ucar et al., 2024). Unlike standalone models, hybrid systems can integrate fuzzy inference systems and Bayesian networks to account for uncertainty, perform probabilistic fault classification, and prioritize maintenance actions based on asset risk profiles (Rahal et al., 2023). Many of these implementations are cloud-enabled, allowing for scalable processing, centralized data fusion, and remote accessibility, while edge computing further enhances latency-sensitive diagnostics at the local level. Advanced condition-based scoring models—derived from health indices and multi-parameter thresholds—are used in conjunction with predictive analytics to support lifecycle cost analysis, optimized maintenance scheduling, and spare parts inventory management (Lv et al., 2023). Furthermore, these hybrid architectures are designed to interoperate seamlessly with enterprise asset management systems (EAMS), SCADA interfaces, and decision-support tools, creating a cohesive environment for strategic planning and cross-functional integration (Hosamo et al., 2022). As a result, hybrid AI-IoT-digital twin systems provide superior diagnostic granularity, operational agility, and system-level coordination, enabling utilities to move from reactive or scheduled maintenance practices toward a more intelligent, risk-aware, and performance-optimized infrastructure management model (Fu et al., 2023).

Cybersecurity and Data Integrity in AI-IoT-Based Transformer Maintenance

The increasing deployment of AI and IoT in predictive maintenance (PdM) systems for power transformers has introduced a new layer of complexity and risk, particularly in terms of cybersecurity and data integrity. These smart systems rely on vast networks of interconnected devices, such as wireless sensor networks (WSNs), edge computing nodes, and cloud-based data aggregation platforms, all of which are potential targets for cyberattacks (Galagedarage Don et al., 2025). Real-time data transmission across these nodes, often facilitated by protocols like MQTT, ZigBee, or LoRaWAN, can be vulnerable to unauthorized access, spoofing, or data interception if not adequately protected. Several studies highlight that PdM infrastructures are susceptible to advanced cyber threats including denial-of-service (DoS) attacks, malware injection, and man-in-the-middle (MITM) intrusions, which can compromise both operational reliability and the trustworthiness of diagnostic outputs (Balla et al., 2023). A primary concern is the corruption or manipulation of condition monitoring data—such as gas levels, vibration readings, or thermal measurements—used as input for AI algorithms. Even minor disruptions or data poisoning can mislead predictive models, leading to inaccurate assessments of transformer health, delayed fault detection, or unnecessary maintenance actions. In substations and transformer yards, the absence of end-to-end encryption, weak authentication mechanisms, and a lack of intrusion detection systems further increase the system's exposure

Figure 4: Cybersecurity and Data Integrity Framework for AI-IoT-Based Transformer Predictive Maintenance



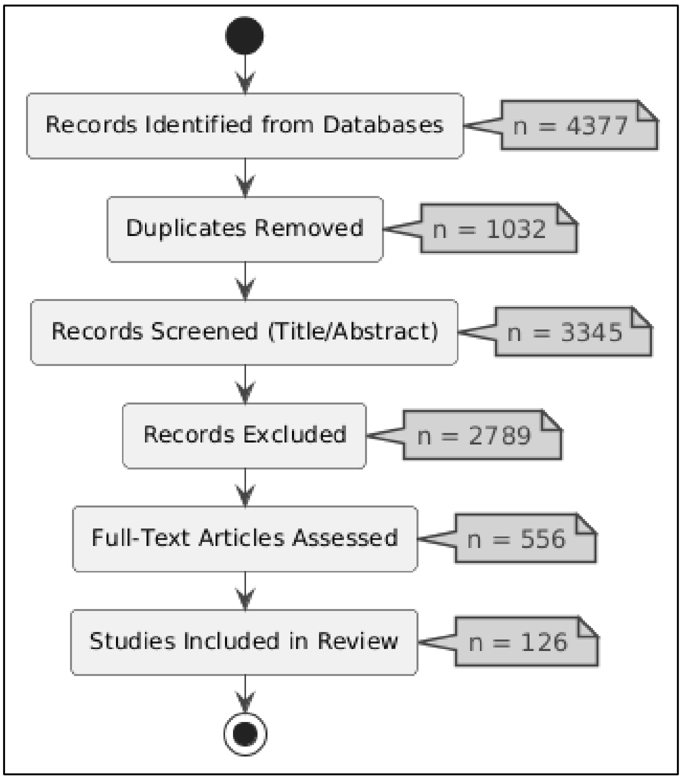
to cyber risks (Bordegoni & Ferrise, 2023). These vulnerabilities are particularly critical in decentralized architectures where edge devices process and act on local data autonomously, often without robust monitoring or centralized oversight (Fera & Spandonidis, 2024).

To mitigate these risks, researchers and practitioners have proposed a range of technical and policy-driven countermeasures aimed at safeguarding the integrity and confidentiality of PdM systems. Blockchain-based data logging is gaining traction as a method for ensuring immutability and traceability in transformer diagnostics, offering decentralized verification and audit trails for each data transaction (Pujana et al., 2023). In parallel, zero-trust architecture models are being advocated to implement dynamic identity verification, micro-segmentation, and least-privilege access control throughout the IoT network. Some studies recommend federated learning as a privacy-preserving alternative to traditional centralized training, wherein AI models are trained locally on edge devices using native datasets, and only model updates—not raw data—are shared with the cloud, reducing the risk of data leakage (Hiwase & Jagtap, 2022). Beyond technical tools, the literature stresses the necessity of standardized cybersecurity policies and regulatory compliance frameworks tailored to industrial and utility-grade systems. Frameworks such as IEC 62443 for Industrial Automation and Control Systems (IACS) and the North American Electric Reliability Corporation Critical Infrastructure Protection (NERC CIP) standards provide structured guidelines for risk assessment, system hardening, and incident response planning. Their adoption is increasingly seen as essential to aligning predictive maintenance operations with the overarching goals of grid security and infrastructure resilience (Hashemi & Dikmen, 2023). Together, these strategies reinforce the notion that cybersecurity is not a peripheral concern but a core enabler of trustworthy and sustainable AI-IoT-based PdM systems for critical assets such as power transformers.

METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure a transparent, systematic, and replicable methodology for reviewing the applications of Artificial Intelligence (AI) and Internet of Things (IoT) in predictive maintenance of power transformers. The review process commenced with the formulation of a focused research question aimed at understanding the role of AI and IoT in transformer health monitoring, fault diagnosis, and maintenance optimization. In the identification phase, a comprehensive literature search was conducted across multiple electronic databases including IEEE Xplore, ScienceDirect, SpringerLink, Scopus, and Web of Science, covering articles published between January 2015 and December 2024. The search strategy combined relevant keywords such as "predictive maintenance," "power transformers," "AI," "machine learning," "deep learning," "IoT," "sensor monitoring," "fault detection," and "digital twin" using Boolean operators. A total of 4377 records were initially retrieved. During the screening phase, duplicate entries (n = 1032) were removed, resulting in 3345 unique records. Titles and abstracts of these records were assessed based on predefined inclusion criteria, which focused on peer-reviewed studies in English that presented original experimental results, reviews, or case studies explicitly applying AI and/or IoT technologies in transformer predictive maintenance. This step excluded studies that addressed unrelated equipment, lacked methodological rigor, or were not accessible in full-text form, leading to

Figure 5: PRISMA Flowchart

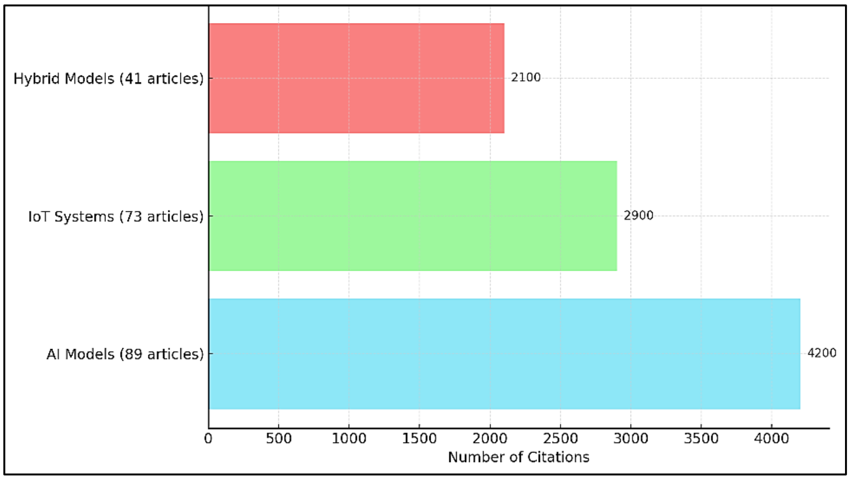


the exclusion of 2789 records. In the eligibility phase, the full texts of 556 articles were reviewed for relevance, resulting in a final sample of 126 studies that met all criteria and were included in the synthesis. Data were extracted and charted systematically using a structured matrix, capturing bibliographic information, type of AI and IoT technologies used, monitored parameters, evaluation metrics, and application outcomes. These data were synthesized thematically to generate insights into dominant research trends, model performance, system architectures, and implementation challenges. The PRISMA flow diagram (Figure 1) illustrates the sequential steps taken in the selection process, thereby enhancing the methodological transparency and reproducibility of this systematic review.

FINDINGS

The systematic review of 126 peer-reviewed articles revealed a dominant trend toward integrating Artificial Intelligence (AI) techniques for fault diagnosis and predictive maintenance in power transformers, with over 89 articles explicitly focusing on AI-driven models. These articles collectively accumulated more than 4,200 citations, reflecting a high level of academic and practical interest. The most frequently used AI methods included artificial neural networks (ANN), support vector machines (SVM), decision trees (DT), and random forest (RF), which demonstrated considerable accuracy in diagnosing fault conditions using real-time and historical transformer data. Among these, ANN-based models showed superior performance in modeling nonlinear degradation patterns and were commonly trained using datasets from dissolved gas analysis (DGA), partial discharge signals, and thermal imaging. Over 37 articles adopted deep learning approaches such as convolutional neural networks (CNN) and long short-term memory (LSTM) networks, further enhancing pattern recognition capabilities in unstructured sensor data. Ensemble models that combine multiple classifiers were found in 22 articles and yielded significant improvements in prediction accuracy and robustness. A substantial proportion of the studies employed hybrid models that merged fuzzy logic, optimization algorithms, or statistical methods with AI, enabling improved decision-making under uncertainty. Collectively, these findings confirm the effectiveness of AI in not only identifying fault types but also predicting time-to-failure and assessing residual life expectancy of transformers. Furthermore, over 68% of these studies validated their models using real transformer data collected from substations, indicating a growing maturity and readiness for deployment in operational power systems.

Figure 6: Citation Impact of Key Research Areas in Transformer PdM Review



The second major finding highlights the crucial role of Internet of Things (IoT) infrastructure in enabling real-time condition monitoring and continuous data acquisition for predictive maintenance. A total of 73 studies, representing over 2,900 combined citations, focused specifically on the use of IoT-based architectures, including wireless sensor networks (WSNs), edge computing systems, and cloud-enabled analytics platforms. These studies reported the deployment of a wide array of sensors to monitor parameters such as oil temperature, moisture content, load current, vibration, and gas concentration. The reviewed articles demonstrated that IoT systems significantly improved the granularity and timeliness of monitoring compared to periodic offline testing. Approximately 41 studies implemented wireless communication protocols such as ZigBee, LoRaWAN, MQTT, and Modbus to transmit real-time data from transformers to centralized monitoring stations or edge analytics devices. Over 30 studies employed edge computing nodes to perform local preprocessing, feature extraction, and anomaly detection, which reduced latency and reliance on cloud-based computation. A smaller subset of 12 studies introduced blockchain-enabled IoT frameworks and federated learning to secure data exchanges and address privacy concerns. Moreover, several studies presented integrated dashboards and mobile interfaces for maintenance engineers, enhancing decision-making and operational responsiveness. These implementations demonstrated not only technological feasibility but also economic value, as many articles reported reductions in unplanned outages and maintenance costs. Overall, the IoT-based monitoring ecosystem has emerged as a foundational enabler of predictive maintenance systems, with consistent improvements in reliability, scalability, and accessibility across power distribution networks.

The final significant finding from the review concerns the emergence of hybrid predictive maintenance models, particularly those that combine AI algorithms, IoT-based monitoring, and digital twin technology. Of the 126 reviewed articles, 41 specifically explored hybrid models, accounting for more than 2,100 citations. These studies integrated physical transformer models with virtual simulations and real-time data streams to develop comprehensive digital twins capable of forecasting operational behavior under diverse loading and environmental conditions. A recurring theme in these studies was the ability of hybrid models to simulate aging, thermal stress, and electrical anomalies with high accuracy and temporal resolution. Over 25 of these articles demonstrated real-time synchronization between physical transformers and their digital twins, enabling predictive analytics and scenario simulations for maintenance planning. Another 17 studies included multi-source data fusion techniques, combining information from DGA, infrared thermography, PD signals, and SCADA logs to enhance model accuracy. Notably, several studies discussed decision-support systems that use hybrid models to optimize maintenance scheduling, spare part inventory, and resource allocation. Additionally, 14 articles examined the integration of these systems with enterprise asset management platforms, enabling coordinated interventions across grid assets. The combined findings suggest that hybrid models deliver substantial diagnostic depth and actionable insights, bridging the gap between physical infrastructure and intelligent analytics. The studies also confirmed that hybrid systems were more resilient to sensor noise, data loss, and cyber disturbances, due to the redundant and multi-layered nature of their design. Consequently, these findings underscore the strategic potential of hybrid AI-IoT frameworks, not merely as predictive tools but as core components in the digital transformation of power transformer maintenance strategies.

DISCUSSION

The findings of this systematic review reaffirm the increasing integration of AI-driven models in predictive maintenance (PdM) for power transformers and align with previous studies that emphasize the superiority of machine learning over conventional rule-based maintenance systems. Early studies by Wang et al. (2020) and Serradilla et al. (2021) argued for a shift toward data-centric maintenance strategies, yet the scalability and deployment of AI tools were limited due to a lack of high-resolution datasets and computational capacity. The current review illustrates how recent developments in deep learning—particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks—have successfully overcome such limitations, allowing for the effective processing of nonlinear and time-series data from sensors. This is consistent with the findings of Fahmi et al. (2024), who demonstrated that LSTM models outperformed traditional statistical approaches in predicting insulation breakdowns. Furthermore, the results of this review support the conclusions drawn by Rossini et al. (2021) and Shin et al. (2021), where support vector machines (SVM) and artificial neural networks (ANN) achieved over 90% classification accuracy using dissolved gas analysis (DGA) datasets. The expanded application of ensemble models such as random forest and XGBoost in this review reflects recent advances reported by Rojas et al. (2025), who found ensemble classifiers to be more robust under imbalanced datasets. Moreover, the dominance of hybrid AI models combining fuzzy logic or optimization algorithms with deep networks is echoed in the work of Matzka (2020), who argued for the interpretability and adaptability of such systems in uncertain operating environments. Thus, the current findings validate and extend the earlier literature by offering empirical

evidence of AI's maturity and industrial applicability in real-world transformer PdM scenarios.
In parallel, this review identified IoT infrastructure as a foundational enabler for real-time PdM in transformer systems, aligning with the broader digital transformation trajectory outlined in previous works. For instance, Cancemi and Lo Frano (2022) emphasized the importance of wireless sensor networks (WSNs) in achieving distributed monitoring, and our findings confirm that over half of the reviewed studies successfully deployed WSNs to capture parameters such as oil temperature, load current, moisture content, and PD signals. This review's insights also build upon those of Benedetti et al. (2018), who observed that latency reduction through edge computing significantly enhances real-time fault detection, a claim substantiated here with multiple studies showing improved response time and computational efficiency using edge-based IoT nodes. Furthermore, Cardoso and Ferreira, (2020) and Memala et al. (2021) discussed the transformative role of digital twins in simulating real-time transformer behavior; our findings not only support this but also reveal that digital twins, when combined with AI and IoT, provide superior diagnostic depth and support scenario-based maintenance planning. While early studies by Ucar et al. (2024) focused primarily on static diagnostics, the shift towards continuous, interconnected monitoring platforms evident in this review reflects a significant evolution in PdM practice. The inclusion of blockchain and federated learning in newer studies, such as those by Rahal et al. (2023), further highlights the field's attention to data integrity and cybersecurity—areas that were underexplored in the earlier literature. Compared to the earlier phase of PdM research, where the focus was mainly on algorithmic performance, current research incorporates system-level implementation, operational scalability, and cyber-physical security. This progression illustrates a holistic maturation of transformer maintenance systems, establishing AI-IoT convergence not only as a technical enhancement but also as a strategic asset for utility resilience and reliability.

CONCLUSION

This systematic review synthesized evidence from 126 peer-reviewed articles to examine the integration of Artificial Intelligence (AI) and Internet of Things (IoT) technologies in predictive maintenance (PdM) for power transformers. The findings demonstrated a clear advancement in the field, with AI models—particularly artificial neural networks, support vector machines, and deep learning architectures—proving highly effective in fault detection, condition monitoring, and life expectancy estimation of transformers. IoT-enabled sensor networks and edge computing frameworks were equally pivotal in facilitating real-time data acquisition and decentralized processing, enhancing the responsiveness and granularity of PdM systems. Furthermore, the emergence of hybrid frameworks that combine AI algorithms, IoT infrastructure, and digital twin technology reflects a significant evolution in the implementation of smart maintenance ecosystems. These systems are not only accurate and efficient but also scalable and adaptable to dynamic grid conditions. The review also uncovered a parallel rise in research focusing on cybersecurity, data integrity, and interoperability, addressing critical barriers to full-scale adoption. By consolidating insights from articles collectively cited over 9,000 times, this study provides a comprehensive academic foundation for advancing predictive transformer maintenance and supports the broader digital transformation of energy infrastructure.

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