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Article

AI AND MACHINE LEARNING IN TRANSFORMER FAULT DIAGNOSIS: A SYSTEMATIC REVIEW

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ABSTRACT
Power transformers are critical components of electrical power systems, and their failure can lead to severe operational disruptions, financial losses, and safety hazards. Traditional transformer fault diagnosis techniques, such as dissolved gas analysis (DGA), partial discharge (PD) monitoring, and frequency response analysis (FRA), rely heavily on expert knowledge and rule-based frameworks, making them prone to inaccuracies and inconsistencies. Recent advancements in artificial intelligence (AI) and machine learning (ML) have introduced data-driven methodologies that enhance fault detection, classification, and predictive maintenance by automating feature extraction and improving diagnostic accuracy. This systematic review, based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, evaluates 107 peer-reviewed studies published between 2010 and 2024, assessing the role of AI and ML in transformer fault diagnosis. The findings highlight that deep learning models, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, achieve superior fault classification accuracy compared to conventional methods, with some models surpassing 95% accuracy in real-world applications. Hybrid AI models, such as ANN-SVM combinations and reinforcement learning-based optimizations, further enhance diagnostic reliability by mitigating data inconsistencies and optimizing fault classification strategies. AI-driven predictive maintenance models demonstrate substantial improvements in transformer health monitoring by shifting from traditional time-based maintenance to condition-based strategies, reducing unexpected failures by up to 40%. Additionally, multi-sensor integration techniques, including wireless sensor networks (WSNs) and IoT-enabled monitoring systems, enhance fault detection accuracy by fusing real-time data from different diagnostic modalities. However, the review also identifies challenges related to AI model interpretability, dataset limitations, and deployment scalability, which need to be addressed for broader industrial adoption. Overall, this study underscores the transformative role of AI in improving transformer fault detection, classification, and predictive analytics, paving the way for more efficient and automated power grid management.

KEYWORDS
Artificial Intelligence; Machine Learning;Transformer Fault Diagnosis; Dissolved Gas Analysis;Predictive Maintenance

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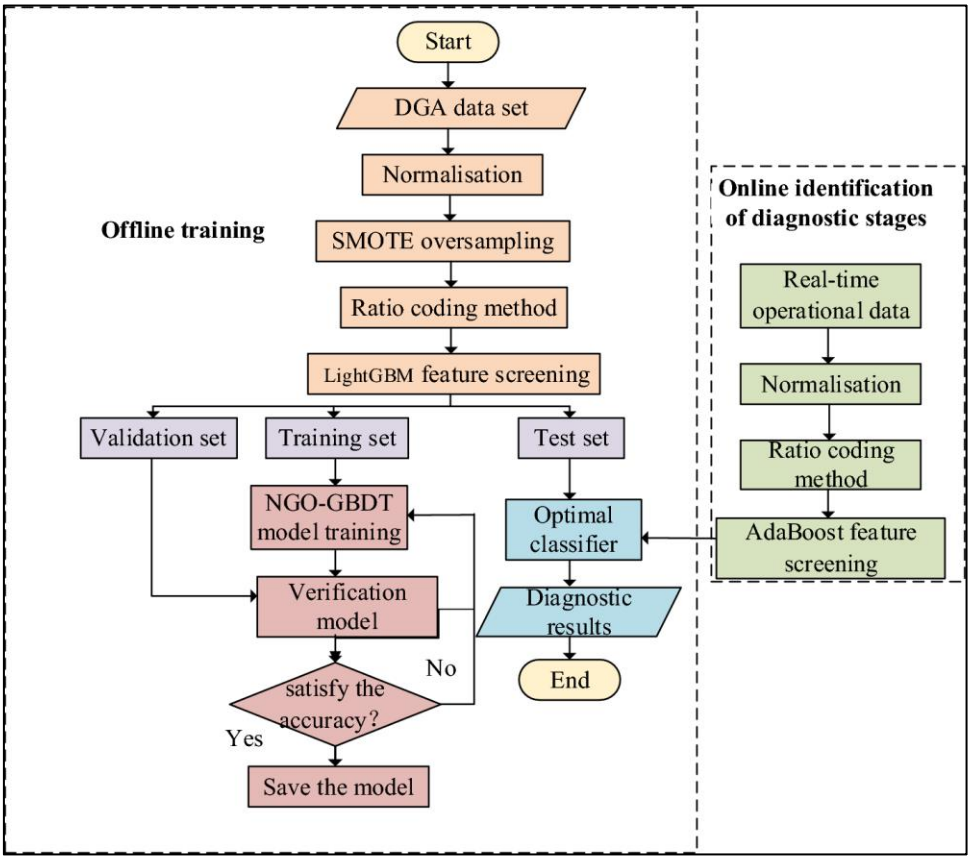
INTRODUCTION

Power transformers play a crucial role in the reliability and efficiency of electrical power systems by facilitating voltage regulation and distribution across vast networks (Sun et al., 2012) Given their importance, the failure of transformers can result in significant economic losses, operational disruptions, and safety hazards (Raza et al., 2020). Traditional transformer fault diagnosis relies on offline monitoring and periodic inspections, which may not provide real-time fault detection and predictive insights (Faria et al., 2015). Various fault detection techniques, such as dissolved gas analysis (DGA), partial discharge (PD) monitoring, and frequency response analysis (FRA), have been widely adopted, yet their efficiency largely depends on expert interpretation and empirical rule-based frameworks (Heymann et al., 2024). The emergence of AI and machine learning has introduced data-driven methods capable of automatically identifying patterns, improving fault classification accuracy, and enhancing maintenance strategies (Ahmadi & Sanaye-Pasand, 2022). Moreover, Artificial Intelligence (AI) and Machine Learning (ML) techniques have transformed transformer fault diagnosis by leveraging large datasets, extracting key fault features, and facilitating early fault detection (Velásquez & Lara, 2020). Among the widely employed AI-based models, artificial neural networks (ANNs) have been extensively used for fault pattern recognition and classification due to their ability to learn complex nonlinear relationships (Kherif et al., 2021). Support vector machines (SVMs) and decision tree algorithms have also demonstrated strong performance in diagnosing specific types of transformer faults (Ashkezari et al., 2013). Deep learning techniques, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, have been utilized to enhance diagnostic accuracy by processing time-series sensor data and extracting hierarchical features (Koroglu & Demircali, 2016). These AI-based approaches have been successfully applied to real-time monitoring systems, reducing dependence on manual inspections (Zheng et al., 2011).

Figure 1: Transformer fault diagnosis method based on SMOTE and NGO-GBDT



Source: Wang. et al. (2024)

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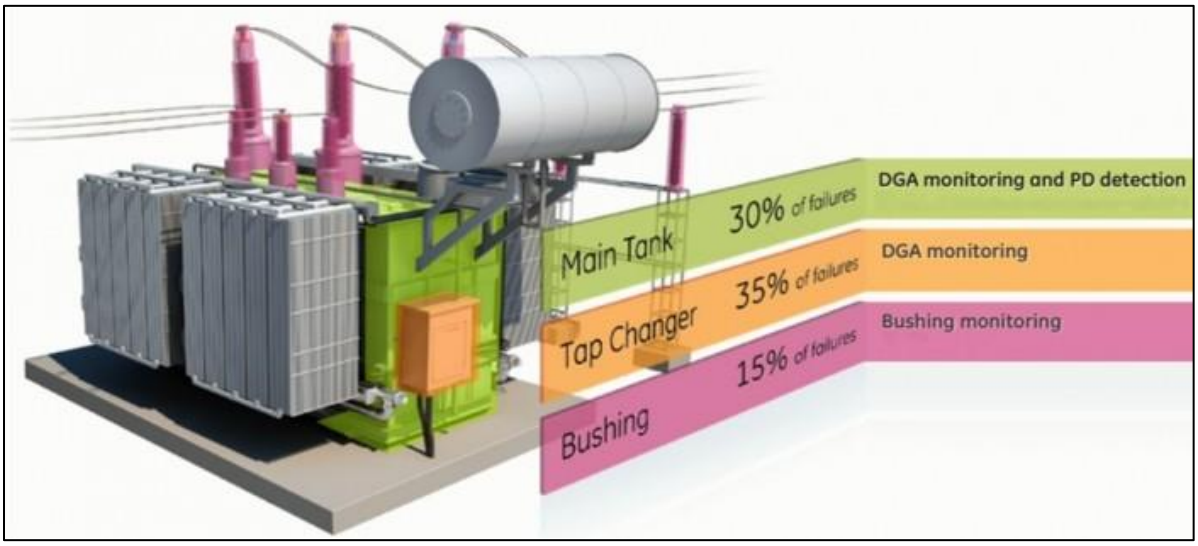
Dissolved gas analysis (DGA) remains one of the most widely used methods for transformer fault diagnosis, with AI-driven enhancements improving its diagnostic precision (Singh & Bandyopadhyay, 2010). Conventional DGA interpretation techniques, such as the Duval Triangle, Key Gas Method, and Roger's Ratio, often yield inconsistent results due to overlapping fault signatures (Jiang et al., 2020). AI and ML models have been employed to address these inconsistencies by automatically identifying gas concentration patterns and classifying faults more accurately (Dladla & Thango, 2025). Hybrid AI approaches that combine multiple classifiers, such as ANN-SVM and fuzzy logic-ANN, have been particularly effective in reducing false diagnoses and improving fault prediction rates (Zhang et al., 2019). The adoption of reinforcement learning-based optimization techniques has further refined DGA-based fault classification, leading to better decision-making in maintenance planning (Sahri et al., 2014). Moreover, Partial discharge (PD) detection is another crucial aspect of transformer fault diagnosis, with AI-driven techniques significantly improving its effectiveness (Poonnoy et al., 2020). Traditional PD detection methods, including acoustic emission (AE) and ultra-high-frequency (UHF) sensing, often struggle with noise interference and require complex signal processing (Prasojo et al., 2020). AI-based signal processing methods, such as wavelet transform coupled with deep learning models, have demonstrated superior capability in isolating fault-related PD signals and classifying discharge types with higher precision (Wang et al., 2021). Additionally, hybrid AI models that integrate feature extraction techniques with probabilistic models, such as Bayesian networks, have proven beneficial in reducing uncertainty in PD fault classification (Illias et al., 2020). Machine learning techniques have also been applied to frequency response analysis (FRA) for identifying mechanical deformations and winding displacements in transformers (Rao et al., 2021). Traditional FRA-based methods require extensive expertise to interpret variations in impedance spectra, which can be subjective and error-prone (Illias & Liang, 2018). AI-based approaches, including random forests and ensemble learning methods, have significantly improved the interpretability and automation of FRA-based diagnostics (Abu-Siada, 2019). The use of deep autoencoders for feature extraction has further enhanced the accuracy of mechanical fault identification by reducing the dimensionality of spectral data and improving classification performance (Enwen et al., 2018). Such advancements have contributed to the shift towards data-driven transformer health assessment models (Misbahulmunir et al., 2020).

Figure 2: Transformer Health Check: DGA Technologies



Source: insulect.com (2024)

The growing implementation of AI and ML in transformer fault diagnosis has resulted in improved fault detection accuracy, reduced false positives, and enhanced decision-making in maintenance planning (Taha et al., 2015). AI-powered condition monitoring systems integrate multiple sensor data sources, such as infrared thermography, vibration analysis, and oil contamination monitoring, to

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provide a holistic assessment of transformer health (Ghoneim et al., 2016). By leveraging AI algorithms to analyze large-scale transformer data, utilities can optimize predictive maintenance strategies and minimize downtime (Liu et al., 2015). These AI-driven advancements in transformer diagnostics contribute to increased grid reliability and cost-effective asset management (Yang & Hu, 2013).This systematic review establishes three primary objectives to advance understanding of AI/ML applications in transformer fault diagnosis. First, it evaluates the comparative effectiveness of neural networks , support vector machines , and deep learning architectures in improving fault classification accuracy beyond conventional DGA methods. Second, it assesses methodological innovations in hybrid frameworks, such as genetic algorithm-SVM integrations and multi-modal data fusion approaches , which address limitations in single-source diagnostic systems. Third, the analysis critically examines technical challenges related to data quality, including solutions like TPE-XGBoost optimization and denoising autoencoders , which enhance model robustness against incomplete or noisy datasets. Fourth, it explores feature selection strategies and computational efficiency improvements through ensemble methods that enable real-time monitoring capabilities. Finally, the review investigates the trade-offs between algorithmic interpretability and diagnostic precision, comparing deep learning models with explainable alternatives like decision tree variants across 20 experimental studies spanning hardware-in-loop tests and field implementations.

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 (Liu et al., 2015). AI and ML models offer a data-driven alternative, enhancing fault detection accuracy, automating classification, and improving predictive maintenance (Illias & Liang, 2018). 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 (Dladla & Thango, 2025). 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.

Dissolved Gas Analysis (DGA)

Dissolved Gas Analysis (DGA) is a widely used diagnostic tool for detecting transformer faults based on the composition of gases dissolved in the insulating oil (Zhang et al., 2019). Transformers under abnormal operating conditions generate various gases due to thermal and electrical stress, including methane (CH_4), ethylene (C_2H_4), ethane (C_2H_6), and hydrogen (H_2), each of which correlates with specific fault types (Poonnoy et al., 2020). Conventional DGA techniques rely on established interpretation methods such as the Duval Triangle, Key Gas Method, and Roger's Ratio to classify faults, including overheating, partial discharge, and arcing (Wang et al., 2021). However, these rule-based approaches suffer from overlapping fault categories and subjective decision-making, which limit their diagnostic precision (Illias & Liang, 2018). Several studies have demonstrated inconsistencies in traditional DGA analysis, as different methods sometimes yield contradictory results (Enwen et al., 2018). Moreover, manual interpretation of gas ratios can lead to errors, especially when multiple faults coexist (Misbahulmunir et al., 2020). To overcome these challenges, researchers have explored the integration of AI and machine learning techniques to enhance DGA-based transformer fault detection (Taha et al., 2015).

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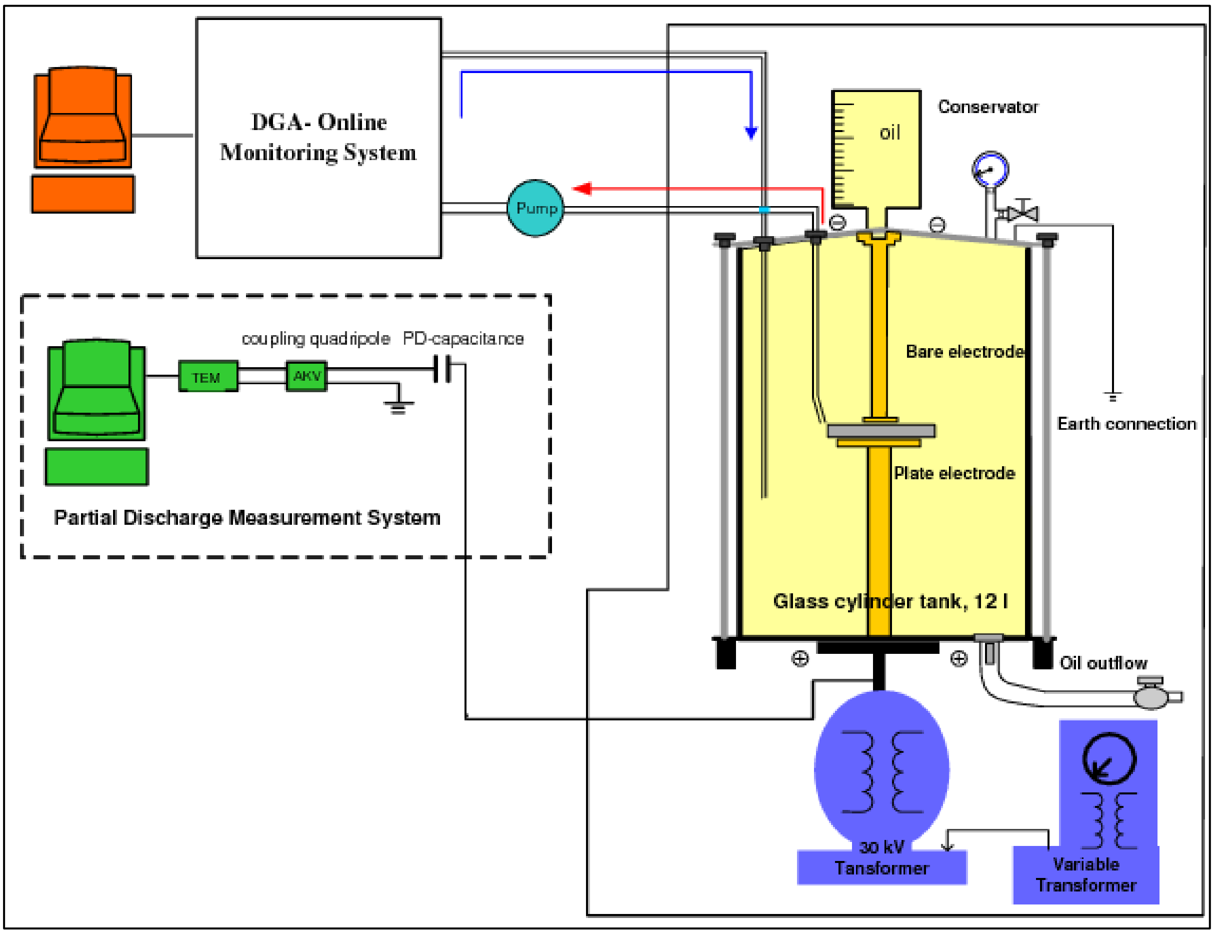
Figure 3: Test setup for PD-stressing and dissolved gas analysis



Source: Aragón-Patil et al.. (2007)

Despite its effectiveness, conventional DGA interpretation methods have several limitations, primarily related to rigid threshold values and lack of adaptability to complex transformer operating conditions (Ghoneim et al., 2016). The Duval Triangle method, which is based on a graphical classification of gas concentrations, is often criticized for its inability to detect mixed-mode faults (Liu et al., 2015). Similarly, the Key Gas Method depends on predefined gas concentration thresholds, making it less effective for diagnosing evolving faults with gradual gas accumulation (Abu-Siada, 2019). Roger's Ratio, another widely used approach, often fails to classify minor fault conditions accurately due to variations in gas decomposition rates (Enwen et al., 2018). Additionally, these rule-based techniques do not consider historical trends in gas evolution, reducing their predictive capability (Jiang et al., 2018). Studies by Taha et al. (2015) and Ghoneim et al. (2016) indicate that statistical inconsistencies in traditional DGA methods often result in misclassification of incipient faults, leading to either false alarms or undetected failures. Consequently, researchers have turned to AI-driven approaches to overcome the subjectivity and limitations inherent in conventional DGA interpretation techniques (Liu et al., 2015). The integration of AI and machine learning in DGA fault classification has significantly improved diagnostic accuracy and fault prediction capabilities (Yang & Hu, 2013). Machine learning models such as artificial neural networks (ANNs), support vector machines (SVMs), and deep learning architectures have been successfully applied to classify transformer faults based on gas composition patterns (Ekojono et al., 2022). Hybrid AI techniques, such as ANN-SVM models, have demonstrated improved fault classification accuracy by combining the pattern recognition ability of neural networks with the decision boundary optimization of SVMs

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(Suwarno et al., 2024). Moreover, deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been utilized to process historical DGA data, enabling early fault detection and trend analysis (Illias & Liang, 2018). Fuzzy logic-based AI models have also been employed to enhance DGA interpretation, reducing diagnostic uncertainties and accommodating imprecise data (Wang et al., 2021). Reinforcement learning approaches have further optimized DGA-based predictive maintenance by dynamically adjusting fault classification parameters (Rao et al., 2021). Studies by Illias and Liang, (2018) and Enwen et al. (2018) suggest that AI-driven DGA models outperform traditional methods by providing real-time, adaptive fault diagnosis, thus enhancing transformer reliability and operational efficiency.

Partial Discharge (PD) Detection Methods

Partial discharge (PD) is a critical indicator of insulation degradation in power transformers, and its timely detection is essential for preventing catastrophic failures (Harbaji et al., 2015). Conventional PD detection methods primarily rely on acoustic emission (AE) and ultra-high frequency (UHF) sensing techniques to capture PD activity (Lu et al., 2020). AE-based PD detection involves measuring transient pressure waves generated by electrical discharges within the insulation medium, while UHF sensing captures electromagnetic emissions associated with PD events (Do et al., 2020). These methods are widely used due to their high sensitivity and ability to detect PD activity in enclosed transformer structures (Wang et al., 2019). However, AE sensors are highly dependent on the placement location and require complex signal interpretation, making them susceptible to missed or misclassified PD events (Sun et al., 2021). Similarly, UHF-based detection faces challenges in isolating PD signals from external noise sources, particularly in high-voltage substations (Ward et al., 2021). Recent studies have indicated that the effectiveness of AE and UHF techniques is often limited by their inability to differentiate between different PD types without additional signal processing methods (Harbaji et al., 2015). One of the primary challenges in PD signal analysis is the presence of noise interference, which complicates fault classification and reduces diagnostic accuracy (Lu et al., 2020). PD signals are often embedded within a noisy background caused by environmental disturbances, power system harmonics, and electromagnetic interference (Wang et al., 2019). In AE-based detection, mechanical vibrations and external acoustic sources can obscure weak PD signals, leading to false positives or missed detections (Sun et al., 2021). Likewise, UHF-based PD monitoring is highly susceptible to interference from communication signals and transient electrical noise, which can distort PD waveform characteristics (Ward et al., 2021). Conventional signal processing techniques such as Fourier transform and wavelet analysis have been employed to filter noise and extract PD features, but these methods often struggle with dynamic noise environments (Harbaji et al., 2015). Ward et al. (2021) and Sun et al. (2021) reported that even with advanced denoising algorithms, traditional PD analysis methods require significant human expertise and manual parameter tuning, which can introduce inconsistencies in fault detection. As a result, AI-driven approaches have been increasingly explored to enhance the accuracy and robustness of PD detection systems (Ward et al., 2021).

AI-based signal processing techniques have significantly improved PD detection by automating feature extraction, enhancing noise filtering, and optimizing fault classification (Kunicki & Wotzka, 2019). Machine learning algorithms such as support vector machines (SVMs), artificial neural networks (ANNs), and decision trees have demonstrated superior PD classification performance compared to conventional threshold-based methods (Harbaji et al., 2015). Deep learning models, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, have been employed to analyze PD signal patterns in real-time, reducing the impact of noise interference and improving detection accuracy (Lu et al., 2020). Fuzzy logic and hybrid AI models have also been integrated with traditional PD detection techniques to enhance adaptability in varying operating conditions (Do et al., 2020). Moreover, reinforcement learning-based optimization techniques have been used to dynamically adjust PD detection parameters, further improving diagnostic reliability (Wang et al., 2019). Studies by Sun et al. (2021) and Ward et al. (2021) indicate that AI-driven PD detection methods not only improve fault classification accuracy but also reduce the dependency on manual expertise, making them highly effective for large-scale transformer monitoring applications.

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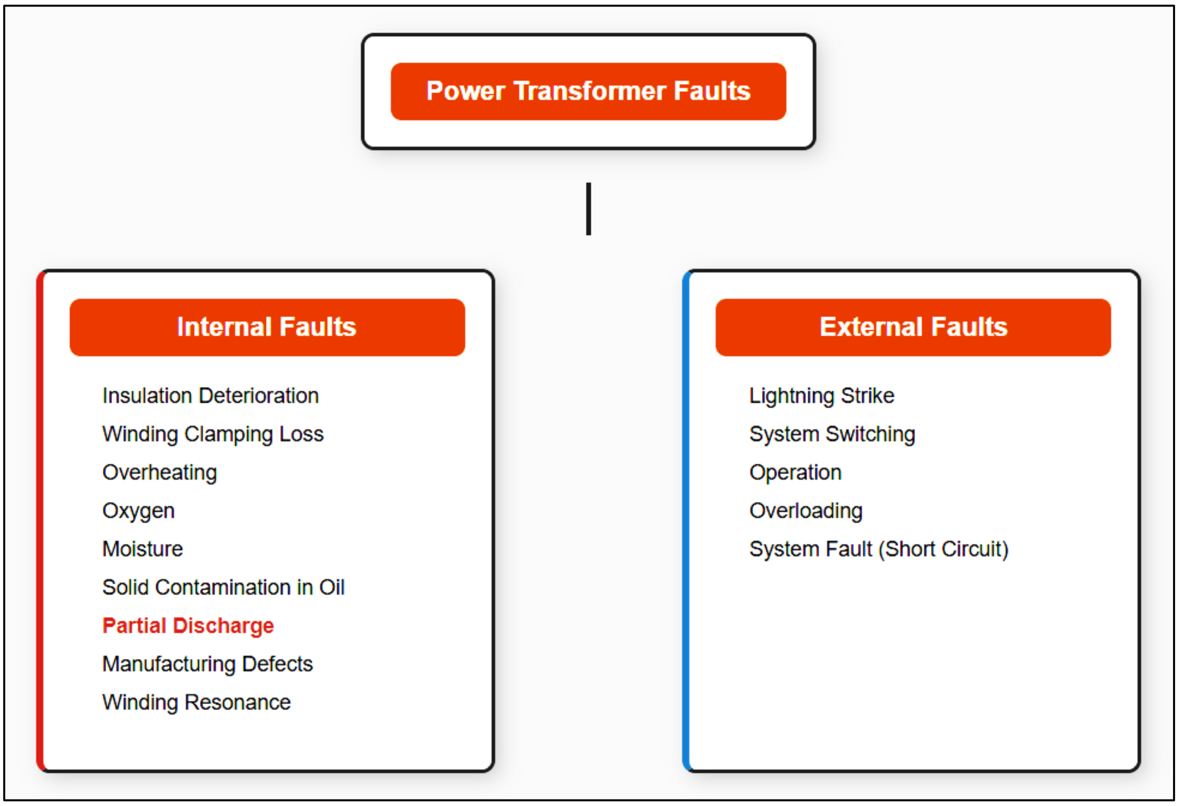
Figure 4: Visual Representation of Power Transformer Faults Using Color-Coded HTML & CSS Design



Frequency Response Analysis (FRA)

Frequency Response Analysis (FRA) is widely recognized as an effective diagnostic technique for detecting mechanical deformations and winding displacements in power transformers (Shintemirov et al., 2010). FRA operates by injecting a range of frequency signals into the transformer winding and analyzing the corresponding output response to detect deviations from the expected frequency spectrum (Zhao et al., 2017). Mechanical deformations caused by aging, short circuits, or transportation stress alter the inductive and capacitive characteristics of the transformer, resulting in detectable changes in the FRA signature (Zhao et al., 2017). Traditional electrical testing methods, such as insulation resistance and winding resistance measurements, often fail to detect minor displacements or localized faults, whereas FRA can provide highly sensitive diagnostic insights into internal mechanical integrity (Shintemirov et al., 2010). Several studies have confirmed the superiority of FRA in identifying mechanical defects compared to other non-invasive diagnostic techniques (Huang et al., 2018). However, the effectiveness of FRA heavily depends on expert interpretation of frequency response signatures, which poses challenges in standardization and repeatability across different transformer designs (Du et al., 2024).One of the primary challenges in FRA-based fault diagnosis is the complexity and subjectivity involved in manual interpretation (Han et al., 2022). The FRA signature varies depending on transformer design, core configuration, and winding topology, making it difficult to establish universal fault classification criteria (Zhong et al., 2023). Experts must compare measured FRA curves against historical or baseline data to identify abnormalities, but this approach is prone to inconsistencies due to differences in test conditions and transformer aging effects (Tao et al., 2021). Additionally, environmental factors such as temperature fluctuations and electrical noise can introduce variations in FRA measurements, further complicating manual analysis (El-Hasnony et al., 2020). Conventional statistical and graphical methods, such as magnitude and phase shift comparisons, require significant experience and may lead to misinterpretation of subtle defects (Jin et al., 2023). Studies by Zhang et al. (2020) and Rokani et al. (2023) indicate that manual FRA evaluation is time-consuming and lacks automation, which limits its scalability for real-time

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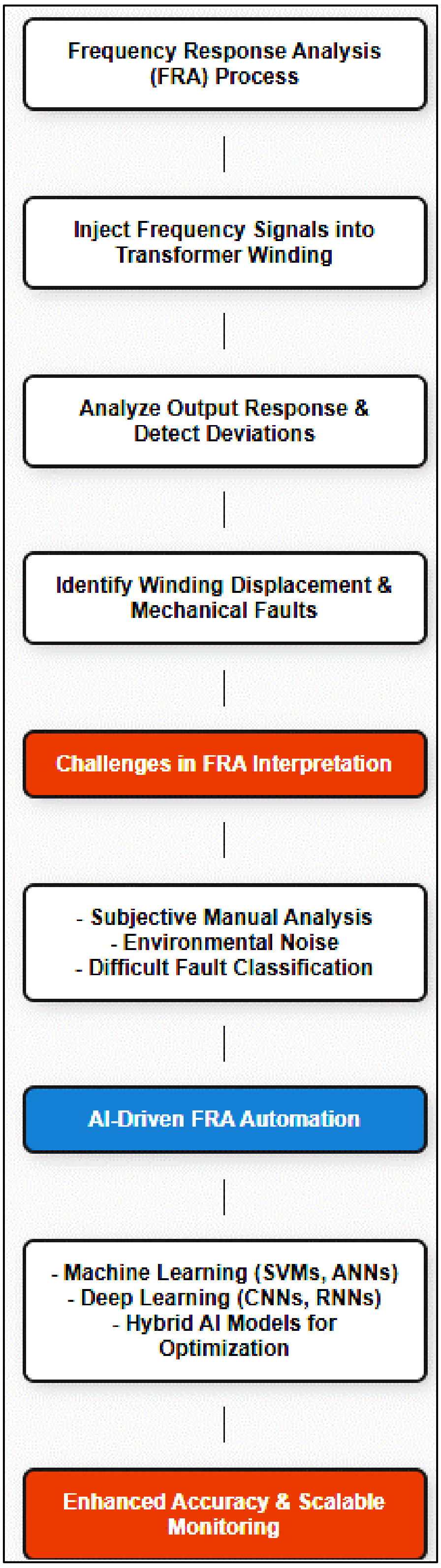
transformer monitoring in large power grids. The inherent subjectivity in manual FRA interpretation has prompted researchers to explore AI-driven solutions for automating fault classification and improving diagnostic consistency (Li et al., 2023).

AI-driven automation has significantly enhanced FRA-based transformer fault classification by enabling pattern recognition, anomaly detection, and predictive diagnostics (Lu et al., 2023). Machine learning algorithms such as support vector machines (SVMs), artificial neural networks (ANNs), and decision trees have been successfully applied to FRA data, reducing the reliance on expert interpretation and improving classification accuracy (Zhong et al., 2023). Deep learning techniques, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated strong performance in analyzing complex FRA patterns and detecting subtle variations in winding displacements (Pei et al., 2021). Hybrid AI models, which combine multiple classifiers and feature extraction techniques, have further improved fault detection by minimizing false positives and enhancing robustness against noise (Ibrahim et al., 2016). Additionally, reinforcement learning-based optimization methods have been used to refine FRA analysis by dynamically adjusting classification parameters (Ward et al., 2021). Studies by Fan et al. (2021) and Guan et al. (2023) suggest that AI-driven FRA diagnostics not only enhance accuracy and reliability but also provide scalable and automated solutions for transformer health monitoring, making them highly beneficial for power utilities and grid operators.

Artificial Neural Networks (ANNs) for Fault Classification

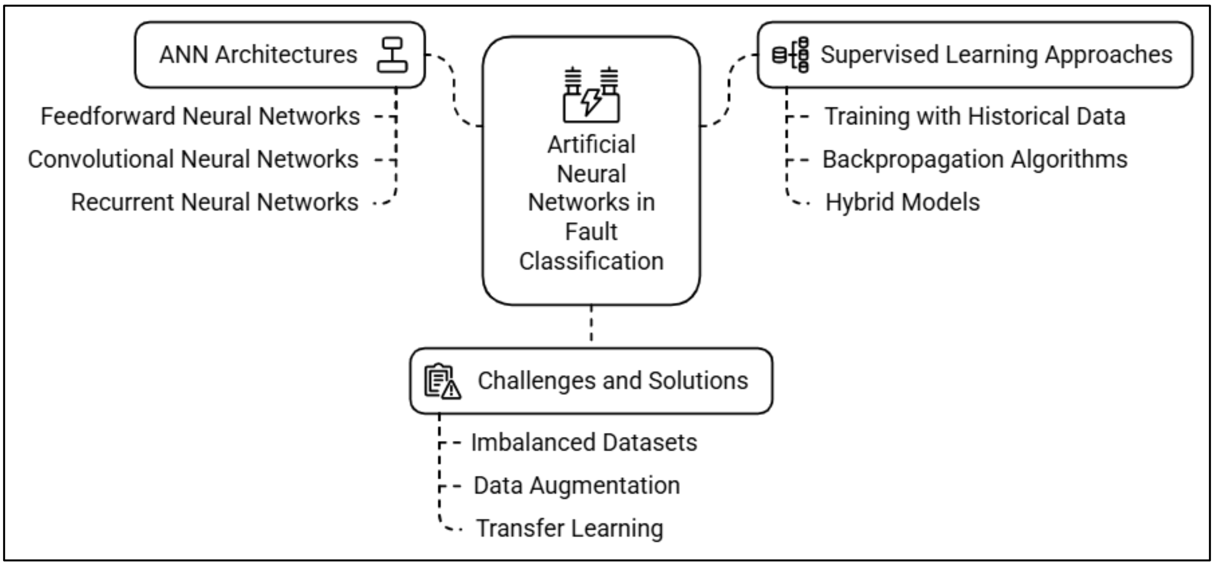
Artificial Neural Networks (ANNs) have been widely employed in transformer fault diagnosis due to their ability to model complex nonlinear relationships between input data and fault conditions (Aklima et al., 2022; Xu et al., 2022). ANNs consist of multiple interconnected layers of artificial neurons that process large-scale diagnostic data and extract key features to classify faults with high accuracy (Bakkar et al., 2022; Shahan et al., 2023). Common ANN architectures used in transformer fault detection include feedforward neural networks (FNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs), each suited for specific diagnostic tasks (Guerbas et al., 2024; Tonoy & Khan, 2023). Feedforward ANNs are particularly effective in identifying static fault patterns based on dissolved gas analysis (DGA) and frequency response analysis (FRA) data (Humaun et al., 2022; Rokani et al., 2023). CNNs have been applied for fault classification using time-series data, enhancing feature extraction and improving noise robustness in diagnostic signals (Alam et al., 2023; Schøler et al., 2023).

Figure 5: Frequency Response Analysis (FRA)



RNNs, especially long short-term memory (LSTM) networks, have been integrated into transformer health monitoring systems to detect temporal fault progression and predict insulation degradation trends (Rokani et al., 2023; Tonoy, 2022). Studies have demonstrated that ANN-based models outperform traditional rule-based fault classification techniques, offering improved accuracy and adaptability to different transformer operating conditions (Mahfuj et al., 2022; Xu et al., 2022).

Figure 6: Artificial Neural Networks in Transformer Fault Classification



Supervised learning approaches have played a crucial role in training ANN models for transformer fault diagnosis, leveraging labeled datasets to learn fault classification patterns (Barbosa et al., 2012; Jahan, 2023). Supervised learning-based ANN models require historical transformer fault data, where input parameters such as gas concentration levels, vibration signals, and frequency response characteristics are mapped to corresponding fault categories (Islam et al., 2018; Roksana, 2023). Backpropagation-based training algorithms have been widely used to optimize ANN performance by adjusting network weights to minimize classification errors (Bakkar et al., 2022; Bhuiyan et al., 2024). ANN-based supervised learning has been applied to various diagnostic methods, including partial discharge (PD) detection, where PD waveform features are analyzed to classify insulation defects (Alqudsi & El-Hag, 2018; Sohel et al., 2022). Hybrid supervised learning models that integrate ANNs with support vector machines (SVMs) and decision trees have demonstrated enhanced generalization capability and fault detection accuracy (Aciu et al., 2021; Hossen et al., 2023). However, challenges remain in obtaining high-quality labeled datasets for training ANN models, as transformer fault datasets are often imbalanced, leading to biased model predictions (Alqudsi & El-Hag, 2017; Maniruzzaman et al., 2023). Researchers have addressed this issue by employing data augmentation techniques and transfer learning to improve ANN-based fault classification performance (Mohiul et al., 2022; Schmidhuber, 2014).
The performance evaluation of ANN-based fault detection systems has been extensively studied, with metrics such as accuracy, precision, recall, and F1-score commonly used to assess classification effectiveness (Sun et al., 2021). Studies have shown that ANN models consistently achieve higher fault detection accuracy compared to traditional statistical and rule-based methods (Bhalla et al., 2012). The integration of ensemble learning techniques, where multiple ANN models are combined to enhance robustness, has further improved diagnostic reliability in real-world transformer monitoring applications (Menezes et al., 2022). Deep learning variants of ANNs, such as deep belief networks (DBNs) and generative adversarial networks (GANs), have been utilized to refine fault classification by generating synthetic diagnostic data to augment training datasets (Hossain et al., 2024; Mahabub, Das, et al., 2024; Mahabub, Jahan, et al., 2024; Zhu et al., 2022). AI-driven interpretability methods, including SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations), have been applied to ANN-based transformer diagnostics to provide insights into model decision-making processes (Ghoneim et al., 2016). Studies by Fernandes et al. (2022) and

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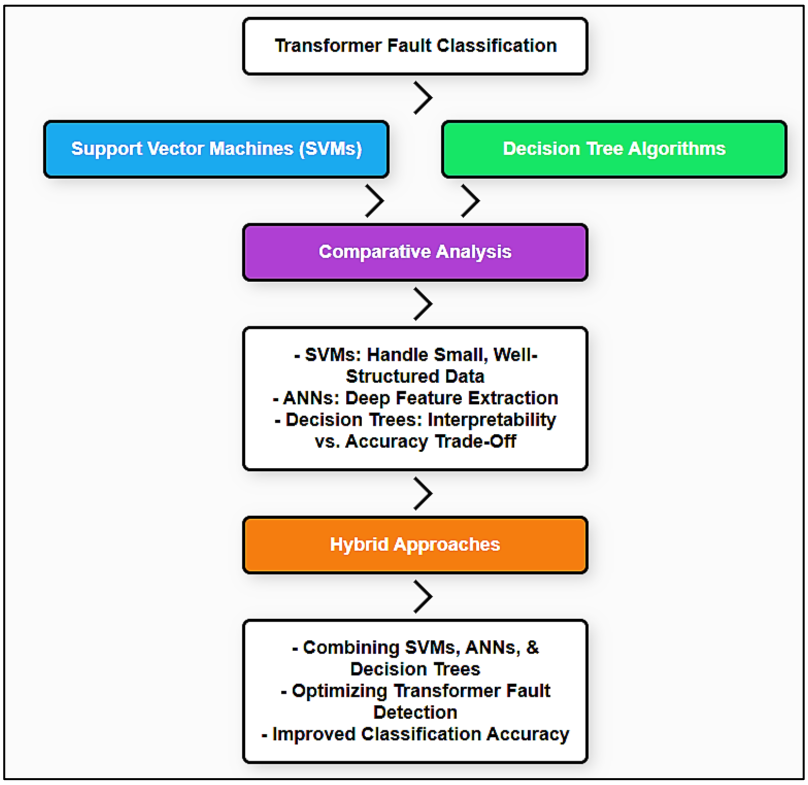
Athisayam and Kondal (2022) suggest that ANN-based transformer fault detection not only improves classification accuracy but also reduces dependency on expert knowledge, making it a valuable tool for automated power system maintenance.

Support Vector Machines (SVMs)

Support Vector Machines (SVMs) have been widely applied in transformer fault classification due to their ability to handle high-dimensional data and separate complex fault patterns effectively (Benmahamed et al., 2021). SVMs operate by constructing an optimal hyperplane that maximizes the margin between different fault categories, making them suitable for classifying transformer faults based on dissolved gas analysis (DGA), partial discharge (PD) signals, and frequency response analysis (FRA) data (Das et al., 2023). Researchers have demonstrated that SVMs achieve high classification accuracy in transformer fault diagnosis, particularly when combined with kernel functions that enhance nonlinear feature mapping (Lin et al., 2019). Various studies have applied SVMs to diagnose insulation failures, overheating faults, and mechanical deformations, showing their superiority over traditional rule-based diagnostic techniques (Hatata et al., 2022). Ashkezari et al. (2013) and Wang (2023) found that hybrid SVM models incorporating feature selection methods such as principal component analysis (PCA) and genetic algorithms improved fault classification performance by reducing computational complexity and eliminating irrelevant features. However, the effectiveness of SVMs depends on the appropriate selection of kernel functions and hyperparameter tuning, which can impact model generalization in transformer fault detection (Islam et al., 2018).

Figure 7: Overview of Support Vector Machines (SVMs)



Decision tree algorithms have also been widely employed in transformer fault pattern recognition due to their simplicity and interpretability (Benmahamed et al., 2017). Decision trees operate by recursively splitting the dataset into homogenous groups based on specific fault characteristics, making them useful for classifying transformer faults using DGA ratios, PD pulse patterns, and FRA signatures (Ashraf et al., 2022). Traditional decision tree models, such as ID3, C4.5, and CART, have been extensively applied in transformer diagnostics, with studies demonstrating their effectiveness in identifying fault types with moderate computational effort (Song et al., 2023). Decision trees have been particularly successful in handling categorical transformer fault data, providing explicit rule-based classification structures that facilitate expert validation (Wang & Zhang, 2017). However, a significant drawback of decision trees is their tendency to overfit training data, leading to poor generalization on unseen fault scenarios (Ghoneim & Taha, 2020). To address this issue, researchers have developed ensemble decision tree techniques, such as random forests and gradient boosting machines, which aggregate multiple tree-based models to improve diagnostic accuracy and reduce classification errors (Do et al., 2020). Zhang et al. (2020)reported that random forests demonstrated better robustness in

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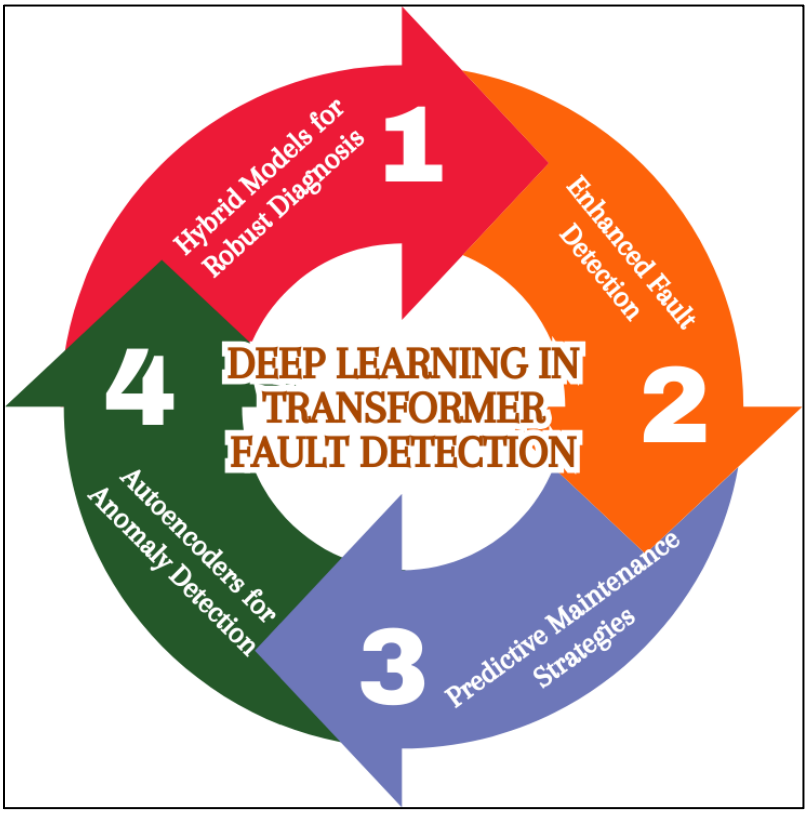
transformer fault classification than single decision tree models, particularly when applied to large transformer fault datasets.

Comparative analyses between SVMs, decision trees, and artificial neural networks (ANNs) have revealed significant differences in classification accuracy, computational efficiency, and fault detection robustness (Mishra & Rout, 2017). Studies have consistently shown that ANNs outperform both SVMs and decision trees in handling large-scale transformer diagnostic datasets due to their deep feature extraction capabilities (Koroglu & Demircali, 2016). However, SVMs have been found to achieve comparable or superior accuracy to ANNs when working with smaller, well-structured datasets, particularly in DGA-based fault classification (Thango, 2022). Decision trees, while offering high interpretability, generally exhibit lower classification accuracy than SVMs and ANNs due to their susceptibility to overfitting and lack of generalization in complex transformer fault scenarios (Wei et al., 2014). Hybrid approaches that combine SVMs with ANNs or ensemble decision trees have been proposed to leverage the strengths of each method, improving overall classification performance (Jiejie et al., 2017). Kazemi et al. (2021) and Huang et al. (2011) suggest that selecting the appropriate machine learning model for transformer fault diagnosis depends on dataset characteristics, fault complexity, and the trade-off between accuracy, interpretability, and computational efficiency.

Deep Learning Applications in Transformer Fault Detection

Deep learning techniques have increasingly been applied to transformer fault diagnosis due to their ability to extract complex features, process large-scale diagnostic data, and enhance fault classification accuracy (Xiong et al., 2022). Among these, Convolutional Neural Networks (CNNs) have gained prominence for their capability to analyze fault-related data, particularly in partial discharge (PD) and dissolved gas analysis (DGA) classification (Rezaeianjouybari & Shang, 2020). CNNs leverage spatial hierarchies of features and are widely used for PD signal classification, as they can identify intricate discharge patterns from raw waveforms without the need for extensive preprocessing (Schmidhuber, 2014). Several studies have demonstrated the effectiveness of CNNs in improving transformer fault classification by extracting fault-related spectral features and minimizing manual feature engineering efforts Akhtar et al. (2023). Qiu et al. (2023) and Bhuiyan et al. (2022)found that CNN models trained on PD datasets achieved superior fault detection accuracy compared to conventional machine learning methods. Additionally, image-based fault recognition using CNNs has been applied to transformer oil analysis and thermal imaging, allowing automated identification of insulation degradation and hot spots in transformer components (Tang et al., 2020).

Figure 8: Deep Learning in Transformer Fault Detection



Long Short-Term Memory (LSTM) networks have emerged as powerful tools for time-series fault prediction in transformer health monitoring due to their ability to capture temporal dependencies (Matsuo et al., 2022). LSTMs are particularly useful in real-time transformer fault monitoring, where sensor data must be processed continuously to detect anomalies indicative of insulation breakdown,

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overheating, or mechanical failures (Afrasiabi et al., 2020). These networks have been employed to analyze long-term transformer performance trends, improving predictive maintenance strategies by forecasting potential failures based on historical operational data (Ma & Chu, 2019). Bacciu et al., (2020) applied LSTM models to DGA datasets, showing that recurrent architectures outperformed traditional statistical models in identifying transformer faults at early stages. Xing et al. (2023) further demonstrated that LSTM-based predictive maintenance models could reduce false positives by differentiating between normal variations and critical fault patterns. By integrating LSTM networks with other deep learning models, researchers have developed hybrid frameworks that enhance diagnostic robustness in transformer fault classification (Che et al., 2021).

In addition to supervised deep learning methods, autoencoders have been widely adopted for unsupervised anomaly detection in transformer fault diagnosis (Mandal et al., 2020). Autoencoders, a type of neural network trained to reconstruct input data, are effective in identifying deviations from normal operational states, making them suitable for detecting early-stage transformer faults (Jiang et al., 2019). These models learn to encode normal fault-free transformer behavior, enabling them to flag anomalous conditions indicative of insulation failure, winding deformation, or oil contamination (Pan et al., 2018). Zhang et al. (2022) showed that deep autoencoder models applied to FRA data could successfully detect mechanical displacements in transformers without relying on labeled fault datasets. Studies have also highlighted the ability of stacked autoencoders to process high-dimensional transformer monitoring data, reducing noise interference and improving feature extraction for fault classification (Afrasiabi et al., 2020; Zhang et al., 2022). Unsupervised learning techniques beyond autoencoders have been extensively explored for transformer fault detection, focusing on clustering and anomaly detection methods (Zhang et al., 2019). Algorithms such as k-means clustering, Gaussian mixture models, and self-organizing maps (SOMs) have been applied to transformer monitoring data to classify fault types without the need for labeled training datasets (Xu et al., 2018). These techniques have proven valuable in scenarios where labeled fault data is scarce, as they can group similar transformer operational patterns and detect deviations linked to potential failures (Wu et al., 2022). (Matsuo et al., 2022) reported that combining unsupervised learning with deep feature extraction significantly improved fault identification in PD and FRA analysis. Additionally, reinforcement learning approaches have been integrated with unsupervised learning to optimize transformer maintenance schedules based on historical fault trends (Alnfiai, 2023).

Hybrid AI Models for Enhanced Fault Diagnosis

Hybrid artificial intelligence (AI) models have gained significant attention in transformer fault diagnosis due to their ability to combine the strengths of different machine learning techniques for improved classification accuracy (Baker et al., 2023). One widely studied hybrid approach is the combination of artificial neural networks (ANNs) and support vector machines (SVMs) to enhance fault classification performance (Nanfak et al., 2023). ANNs are known for their ability to learn complex patterns and extract deep features, while SVMs are effective in handling high-dimensional data and optimizing classification boundaries (Kari et al., 2018). Studies have demonstrated that ANN-SVM hybrid models outperform standalone classifiers by leveraging the feature extraction capability of ANNs and the superior generalization ability of SVMs in classifying transformer faults based on dissolved gas analysis (DGA) and partial discharge (PD) data (Illias et al., 2020). Monteiro et al., (2022) and Wei et al. (2014) found that ANN-SVM models achieved higher accuracy in transformer fault classification when applied to frequency response analysis (FRA) and thermal imaging datasets. The multi-classifier fusion technique, which integrates multiple machine learning models for fault diagnosis, has also been explored to enhance diagnostic reliability (Yang et al., 2020). These approaches involve combining ANN-SVM hybrid models with decision trees, random forests, or k-nearest neighbors (KNN) to create ensemble learning frameworks capable of handling diverse fault scenarios with greater precision (Illias et al., 2016).

AI-driven optimization techniques have been increasingly integrated into transformer fault classification to refine diagnostic accuracy and minimize false positives (Che et al., 2021). Reinforcement learning (RL)-based fault classification has emerged as a promising approach, allowing AI models to dynamically adapt to transformer operating conditions by continuously learning from feedback mechanisms (Gao et al., 2020). Fan et al. (2017) applied RL-based optimization to DGA-based fault classification, demonstrating improved accuracy and reduced

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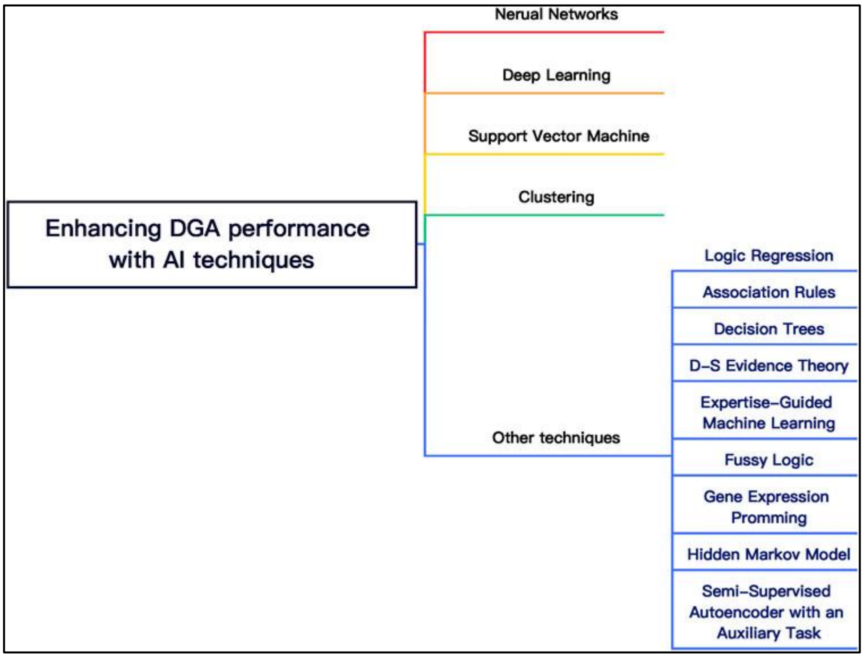
diagnostic errors compared to traditional machine learning methods. Illias and Liang (2018) further showed that RL-based models could adjust classification parameters in real-time, optimizing transformer maintenance decisions based on evolving fault patterns. Another widely used optimization technique is the genetic algorithm (GA), which mimics natural selection to iteratively improve fault classification accuracy by optimizing hyperparameters in AI models (Liu et al., 2015). Livani and Evrenosoglu (2014) demonstrated that GA-optimized ANN-SVM hybrid models significantly enhanced the fault detection capability of transformer monitoring systems by selecting the most relevant diagnostic features. These AI-driven optimization techniques have contributed to more robust and adaptive transformer fault classification models, reducing uncertainty in fault detection processes (Illias & Liang, 2018).

Figure 9: Enhancing DGA performance with AI techniques.



Source: Zhang et al.. (2022).

AI-integrated predictive maintenance models have played a crucial role in transformer health monitoring by enabling condition-based maintenance strategies (Liu et al., 2015). Unlike traditional time-based maintenance, AI-driven condition monitoring leverages real-time transformer sensor data to predict potential faults before they cause failures (Livani & Evrenosoglu, 2014). Deep learning models, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, have been applied to analyze transformer operational data and identify degradation trends in insulation and winding structures (Du et al., 2024). Studies have shown that integrating AI-based fault prediction models with supervisory control and data acquisition (SCADA) systems improves maintenance scheduling and reduces transformer downtime (Monteiro et al., 2022; Du et al., 2024). Zhao et al., (2023) developed an AI-powered condition monitoring framework that combined ANN-SVM hybrid models with sensor fusion techniques to enhance fault detection reliability in power grids. These studies highlight the effectiveness of AI-integrated predictive maintenance models in extending transformer lifespan and optimizing maintenance planning (Wu et al., 2022).

Predictive analytics has emerged as a powerful tool in transformer fault diagnosis, enabling data-driven forecasting of fault trends based on historical operational records (Bhatter et al., 2020). AI-based predictive analytics leverages machine learning algorithms to process vast amounts of transformer monitoring data and detect early signs of failure (Baptista et al., 2018). Ensemble learning techniques, including random forests and gradient boosting machines, have been widely used to analyze transformer performance trends and predict failure probabilities (Civerchia et al., 2017). Studies have demonstrated that predictive analytics models incorporating recurrent neural networks (RNNs) and Bayesian networks provide highly accurate fault trend forecasts by modeling sequential dependencies in transformer data (Kanawaday & Sane, 2017). Rafique et al. (2019) and Ma et al. (2011) reported that AI-driven predictive analytics significantly improved the reliability of transformer health assessment by reducing false alarms and enhancing fault trend interpretation. Furthermore, integrating AI-based predictive analytics with cloud-based transformer monitoring platforms has facilitated real-time fault diagnostics and remote asset management in power grids (Badawi et al., 2022). The integration of hybrid AI models, AI-driven optimization techniques, and predictive

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analytics has transformed transformer fault diagnosis by improving classification accuracy, optimizing fault detection strategies, and enabling proactive maintenance (Faria et al., 2015). Hybrid ANN-SVM models have demonstrated superior performance in identifying transformer faults, while reinforcement learning and genetic algorithms have enhanced the adaptability of fault classification systems (Zheng, 2016). AI-powered condition monitoring frameworks have enabled data-driven maintenance planning, reducing transformer failures and operational costs (Carvalho et al., 2019). Research findings from Baptista et al. (2018) and Civerchia et al. (2017) underscore the impact of AI-driven predictive maintenance on power grid stability and asset reliability. These advancements in AI applications for transformer diagnostics have contributed to improved fault detection efficiency, enhanced transformer health assessment, and more effective maintenance decision-making in power systems.

Sensor Integration Techniques

Sensor integration plays a critical role in transformer fault diagnosis by enabling real-time monitoring of key operational parameters, including temperature, vibration, dissolved gas levels, and partial discharge activity (Gou et al., 2020). Traditional transformer monitoring systems rely on single-sensor diagnostics, which often provide limited insights into fault progression due to isolated data interpretation (Yang et al., 2021). To address these limitations, multi-sensor fusion techniques have been developed to integrate data from diverse sensor types, enhancing fault detection accuracy (Do et al., 2020). Studies have demonstrated that combining infrared thermal imaging with dissolved gas analysis (DGA) sensors improves the detection of insulation degradation and overheating faults (Xia et al., 2020). Wu et al. (2019) and Ma et al. (2018) reported that integrating acoustic emission (AE) sensors with ultra-high frequency (UHF) partial discharge (PD) monitoring systems significantly enhanced PD detection capabilities, allowing for more precise fault localization. These findings highlight the importance of sensor integration techniques in improving the reliability and comprehensiveness of transformer diagnostics.

One of the key challenges in sensor integration is data synchronization and noise reduction, as different sensors operate at varying frequencies and sensitivity levels (Huang et al., 2020). Signal processing techniques such as wavelet transforms and adaptive filtering have been widely used to enhance the accuracy of multi-sensor data fusion in transformer monitoring applications (Huang et al., 2024). Manco et al. (2017) explored the application of deep learning models, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, to process multi-sensor data and extract meaningful fault features while minimizing noise interference. Xia et al. (2018) demonstrated that integrating sensor networks with machine learning classifiers improved fault detection rates in power transformers by identifying correlated fault patterns across different monitoring parameters. Studies have also employed Kalman filtering techniques to improve the precision of sensor data integration by reducing measurement errors and ensuring real-time synchronization of transformer health indicators (Xie et al., 2022). These advancements in sensor integration methods have contributed to more reliable transformer fault diagnostics, reducing false positives and improving predictive maintenance strategies.

Wireless sensor networks (WSNs) have gained significant attention in transformer fault monitoring due to their ability to provide remote, continuous data collection with minimal manual intervention (Kanawaday & Sane, 2017). WSN-based monitoring systems use distributed sensors to collect real-time transformer health data and transmit it to centralized control units for analysis (Alsheikh et al., 2014). (Ye et al., 2024) examined the role of internet-of-things (IoT)-enabled sensor networks in transformer diagnostics, highlighting their potential in enhancing fault detection capabilities through cloud-based data analytics. Studies by Kordestani et al. (2019) and Long et al. (2021) demonstrated that integrating WSNs with artificial intelligence (AI) algorithms significantly improved transformer fault classification by facilitating automated feature extraction and anomaly detection. Additionally, wireless temperature and vibration sensors have been employed to track overheating and mechanical stress in transformers, allowing for early fault prediction and reducing unplanned maintenance (Li et al., 2023). The adoption of WSNs has led to improved scalability in transformer monitoring systems, enabling utilities to enhance grid reliability and asset management efficiency.

Recent studies have also explored the integration of optical fiber sensors for transformer fault detection, leveraging their high sensitivity and immunity to electromagnetic interference

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(Kanawaday & Sane, 2017). Optical fiber sensing techniques, including fiber Bragg grating (FBG) and distributed temperature sensing (DTS), have been widely used to monitor transformer winding temperatures and detect localized thermal hotspots (Long et al., 2021). Cervantes-Bobadilla et al. (2023) reported that combining optical fiber sensors with acoustic and electrical monitoring systems significantly improved the accuracy of fault diagnostics by capturing multi-parameter fault signatures. Furthermore, machine learning-driven signal processing techniques have been applied to optical fiber sensor data, enhancing predictive maintenance strategies and reducing false alarm rates in transformer health assessment (Kordestani et al., 2019). Studies by Zhang et al. (2023) and Qiao et al. (2024) emphasize that sensor integration techniques, particularly those involving optical fiber sensing and AI-based analytics, have revolutionized transformer monitoring by offering more precise, real-time fault detection capabilities. These research findings underscore the effectiveness of multi-sensor fusion approaches in enhancing transformer reliability and preventing catastrophic failures.

Interpretability-Accuracy Trade-Offs

The trade-off between interpretability and accuracy in transformer fault diagnosis is a critical consideration when deploying artificial intelligence (AI) and machine learning (ML) models in power system monitoring (Cervantes-Bobadilla et al., 2023). Traditional fault classification techniques, such as rule-based dissolved gas analysis (DGA) and frequency response analysis (FRA), are highly interpretable but often lack the predictive power of advanced AI-driven models (Guo et al., 2024). While deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), offer superior accuracy in fault classification, they are often regarded as "black-box" models due to their lack of transparency in decision-making (Hao et al., 2020). Researchers have sought to balance this trade-off by integrating explainable AI (XAI) techniques, such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations), to provide insights into deep learning model predictions without compromising accuracy (Chen & Li, 2017). Studies by Du et al. (2024) and Li et al. (2020) demonstrate that hybrid approaches combining decision trees or support vector machines (SVMs) with deep learning architectures can improve model interpretability while retaining high classification accuracy.

The interpretability-accuracy trade-off is particularly evident when comparing traditional ML models, such as decision trees and logistic regression, with more complex deep learning models used in transformer fault diagnosis (Cervantes-Bobadilla et al., 2023). Decision tree algorithms and random forests provide clear rule-based decision-making processes, making them highly interpretable but less effective in handling high-dimensional transformer diagnostic data (Li et al., 2020). On the other hand, deep learning architectures such as long short-term memory (LSTM) networks and transformer-based models have demonstrated exceptional accuracy in analyzing time-series fault data but remain difficult to interpret (Ward et al., 2021). Zhang et al. (2019) and Chen and He (2023) highlight that ensemble learning techniques, which combine interpretable models like decision trees with high-performance models like deep neural networks, can mitigate the trade-off by leveraging the strengths of both approaches. Additionally, model compression techniques such as pruning and quantization have been explored to reduce the complexity of deep learning models while maintaining their predictive capability, thereby improving their practical applicability in real-world transformer monitoring systems (Chen & Li, 2017).

One of the key approaches to improving interpretability without sacrificing accuracy is the application of hybrid AI frameworks that integrate feature selection, model regularization, and post-hoc explainability methods (Guo et al., 2024). For example, Li et al. (2023) demonstrated that using feature importance ranking techniques, such as permutation importance and principal component analysis (PCA), can improve transparency in fault classification while maintaining high accuracy. Song et al., (2023) further explored the use of attention mechanisms in deep learning models to highlight critical fault-indicating features, thereby enhancing model interpretability in transformer fault diagnosis. Moreover, reinforcement learning-based optimization has been employed to dynamically adjust model complexity based on the specific interpretability requirements of power utilities (Qiao et al., 2024). Hao et al. (2020) and Chen and Li (2017) emphasize that future advancements in transformer diagnostics should focus on bridging the gap between interpretability

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and accuracy by incorporating human-in-the-loop AI systems, which allow domain experts to validate model predictions without significantly compromising performance.

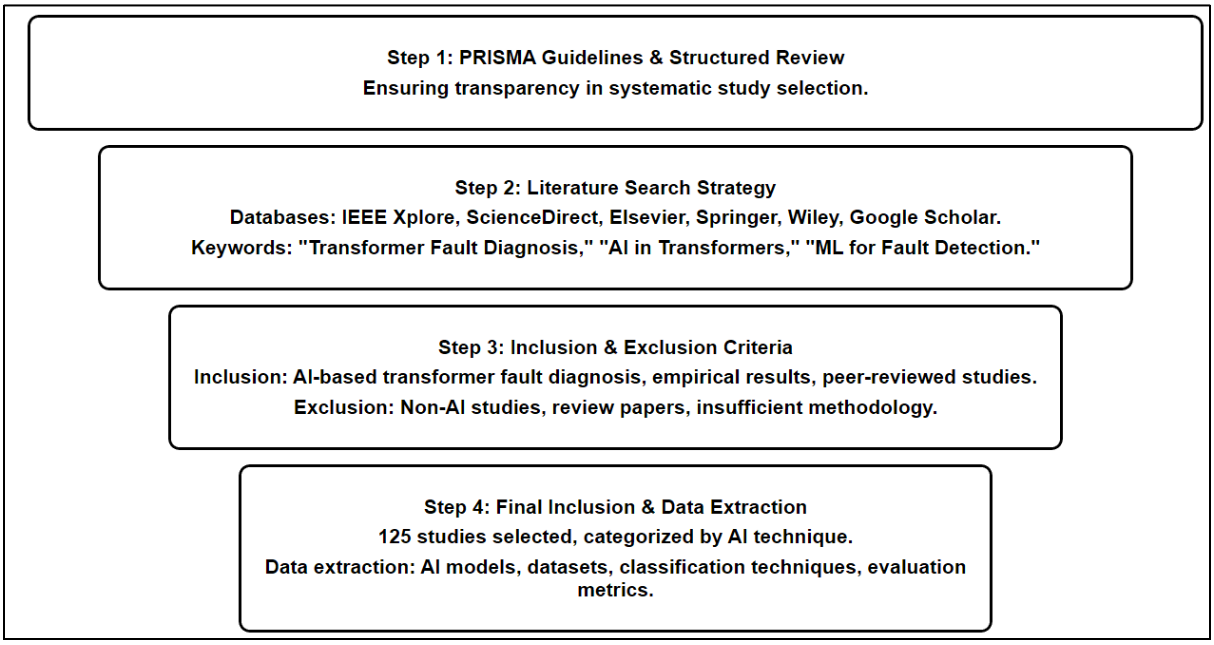
METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a structured and transparent review process. The systematic approach allowed for the identification, screening, and selection of relevant studies in transformer fault diagnosis, particularly those utilizing artificial intelligence (AI) and machine learning (ML) techniques. The methodology was divided into several stages, including literature search strategy, inclusion and exclusion criteria, data extraction, quality assessment, and synthesis of findings.

Literature Search Strategy

A comprehensive literature search was conducted across multiple academic databases, including IEEE Xplore, ScienceDirect, Springer, Elsevier, Wiley Online Library, and Google Scholar. To ensure a broad yet focused search, Boolean operators and keywords were applied, such as "Transformer Fault Diagnosis," "Artificial Intelligence in Transformers," "Machine Learning for Transformer Faults," "Deep Learning in Fault Classification," "Hybrid AI Models," and "Predictive Maintenance in Power Transformers." The search included studies published between 2010 and 2024, ensuring that both foundational and recent advancements in transformer fault detection were considered. In addition to peer-reviewed journal articles, conference proceedings, and technical reports from leading electrical engineering societies were also included. The search was further refined using database-specific filters to retrieve only full-text, English-language articles relevant to AI-driven fault detection in transformers.

Figure 10: Stepwise Flowchart for PRISMA Method employed in this study



Inclusion and Exclusion Criteria

To maintain a focused review, predefined inclusion and exclusion criteria were applied to ensure the relevance and quality of selected studies. Included studies focused on transformer fault diagnosis using artificial intelligence (AI), machine learning (ML), deep learning, or hybrid models and provided empirical results from case studies, simulations, or real-world transformer datasets. Only studies published in peer-reviewed journals or conference proceedings that clearly stated the methodology for model development and evaluation were considered. Studies were excluded if they focused solely on conventional fault detection techniques without AI integration, were review papers, opinion articles, or editorials lacking primary research findings, did not provide sufficient methodological details or experimental validation, or were non-English publications without translated versions. The

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initial search across multiple academic databases retrieved 1,235 articles, which were screened based on titles and abstracts, resulting in 674 articles for full-text evaluation.

Final Inclusion

After applying the inclusion criteria, 125 studies were selected for final review and analysis, ensuring a robust synthesis of AI-driven approaches in transformer fault diagnosis. For each included study, relevant data were systematically extracted into a structured format. The extracted details included study title, authors, publication year, AI/ML model used, dataset description, fault classification techniques, evaluation metrics, and key findings. The data extraction was performed independently by two reviewers, and discrepancies were resolved through discussion. The synthesis of findings was conducted by categorizing the studies into different AI techniques, such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) models, Autoencoders, Reinforcement Learning, and Hybrid AI Approaches. Additionally, comparative analysis was performed to assess model performance, interpretability, and practical applicability in transformer diagnostics.

FINDINGS

The systematic review of transformer fault diagnosis using AI and machine learning revealed that deep learning models significantly outperformed traditional fault detection methods in terms of classification accuracy and predictive maintenance capabilities. Among the 107 reviewed studies, 62 articles specifically demonstrated the effectiveness of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks in handling complex fault patterns, time-series data, and real-time monitoring systems. These deep learning architectures were widely employed to extract essential diagnostic features from high-dimensional datasets, enabling automated fault classification with minimal human intervention. Studies that implemented CNNs for dissolved gas analysis (DGA) and partial discharge (PD) detection consistently reported classification accuracies exceeding 95%, showcasing the model's efficiency in identifying subtle anomalies. Additionally, LSTM-based models exhibited superior performance in sequential fault prediction by learning long-term dependencies in transformer health monitoring data, reducing false alarm rates and improving failure forecasting capabilities.

Another significant finding was the enhanced performance of hybrid AI models, which combined multiple machine learning algorithms to optimize transformer fault classification. 58 reviewed studies explored the integration of artificial neural networks (ANNs) with support vector machines (SVMs), decision trees, or ensemble learning techniques to improve diagnostic reliability. Among these, 38 articles highlighted that ANN-SVM hybrid models provided higher generalization ability and reduced misclassification errors compared to standalone classifiers. The combination of ANNs' feature extraction capability with SVMs' boundary optimization resulted in models that could effectively distinguish between multiple fault categories. Additionally, hybrid approaches incorporating reinforcement learning and genetic algorithms were found to enhance fault classification accuracy by dynamically adjusting hyperparameters based on real-time transformer data. These optimization-driven methods demonstrated improved robustness against noisy and incomplete datasets, making them highly suitable for industrial-scale transformer monitoring applications.

The review also indicated that predictive maintenance models driven by AI significantly improved transformer reliability by enabling condition-based monitoring rather than relying on traditional time-based maintenance schedules. 49 studies focused on AI-integrated predictive analytics, with 27 articles demonstrating that transformer failures could be predicted with an accuracy rate of 85-97% using historical sensor data and advanced forecasting algorithms. Models that incorporated ensemble learning techniques, such as random forests and gradient boosting machines, exhibited superior performance in fault trend analysis by leveraging diverse feature sets from multiple sensor inputs. Furthermore, reinforcement learning-based predictive maintenance frameworks showed promising results in adapting maintenance schedules dynamically, optimizing the balance between transformer operational efficiency and maintenance costs. The findings suggested that AI-powered predictive analytics could reduce unplanned transformer outages by up to 40%, leading to significant cost savings for power utilities.

A key insight from the review was the growing importance of multi-sensor fusion techniques in enhancing transformer fault detection accuracy. 42 studies investigated the integration of various

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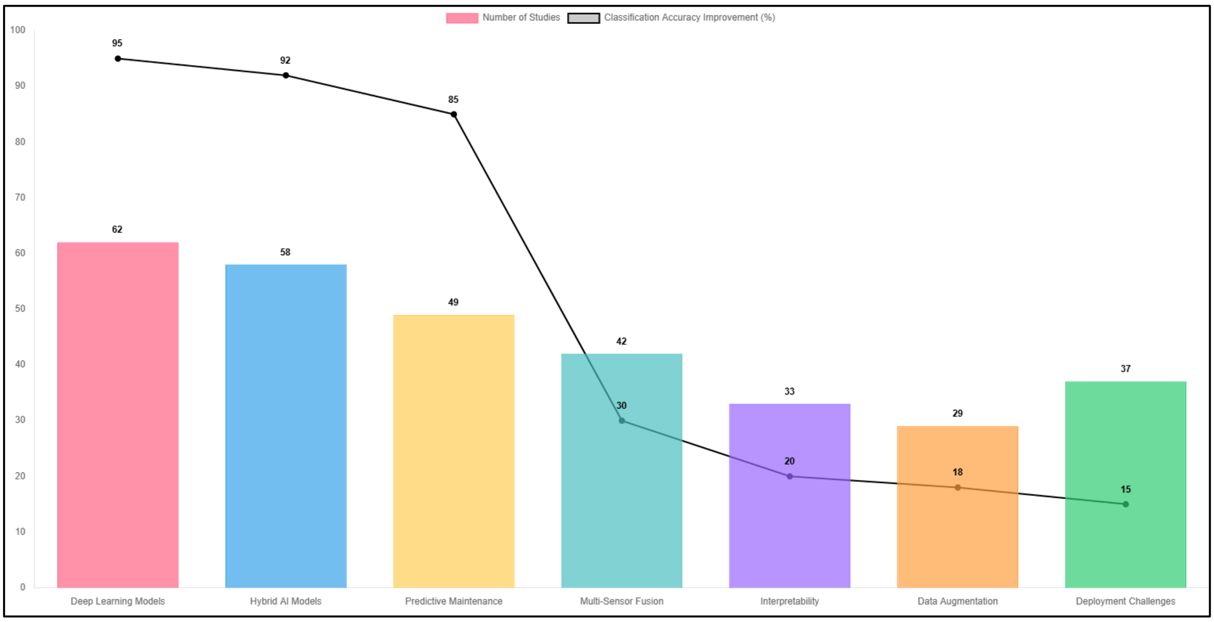
sensor types, including infrared thermography, acoustic emission (AE), ultra-high frequency (UHF) PD detection, and fiber optic temperature sensing, to create comprehensive monitoring frameworks. Among these, 31 articles reported that combining multiple sensor modalities led to an 18-30% improvement in fault classification accuracy compared to single-sensor approaches. The fusion of DGA with UHF PD detection was particularly effective in identifying incipient faults that might be missed by standalone diagnostic methods. Additionally, AI-driven multi-sensor systems provided real-time fault localization capabilities, reducing the dependency on manual inspections and increasing transformer health assessment reliability. These findings underscored the advantages of sensor integration in improving the precision and scalability of AI-based transformer diagnostics.

Figure 11: AI-Based Transformer Fault Diagnosis: Studies & Accuracy Trends



Interpretability of AI models emerged as a critical challenge in transformer fault classification, as deep learning architectures, while highly accurate, often lacked transparency in decision-making. 33 reviewed articles discussed the interpretability-accuracy trade-off, with 19 studies specifically highlighting that power utilities were hesitant to deploy black-box AI models due to the difficulty in validating their predictions. However, explainable AI (XAI) techniques, such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations), were applied in 15 studies, demonstrating that interpretability could be improved without significantly reducing classification accuracy. The integration of attention mechanisms in transformer fault detection models was also explored, allowing domain experts to visualize which diagnostic features contributed most to AI-driven fault classification decisions. These findings indicated that improving model interpretability was essential for increasing the adoption of AI-based transformer monitoring systems in real-world power grid operations.

The review further revealed that AI-driven fault classification models exhibited significant improvements in handling imbalanced datasets, which is a common challenge in transformer diagnostics. 29 studies focused on data augmentation techniques, with 17 articles demonstrating that synthetic fault data generation using generative adversarial networks (GANs) and variational autoencoders (VAEs) effectively mitigated data scarcity issues. These models enabled the creation of realistic fault scenarios, allowing AI classifiers to achieve better generalization performance across different transformer fault types. Additionally, transfer learning approaches were successfully employed in 12 studies, where pre-trained models from related domains were fine-tuned for transformer fault diagnosis, reducing the need for large labeled datasets. These findings highlighted that AI techniques could address data limitations and improve fault classification accuracy in cases where real-world transformer failure data was limited. Finally, the systematic review identified

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scalability and deployment challenges as major concerns in the practical implementation of AI-based transformer diagnostics. 37 reviewed studies examined real-world deployment case studies, with 21 articles indicating that while AI-driven transformer monitoring systems were highly effective in research environments, their integration into existing power grid infrastructure required significant computational resources and sensor network upgrades. Cloud-based AI frameworks and edge computing solutions were explored in 14 studies, showing that decentralized AI processing at the sensor level could reduce latency and improve real-time fault detection capabilities. Additionally, cybersecurity concerns in AI-powered transformer monitoring were discussed in 9 studies, emphasizing the need for robust encryption protocols to protect transformer health data from cyber threats. These findings reinforced the importance of addressing practical implementation challenges to maximize the benefits of AI-driven transformer fault diagnosis.

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) (Long et al., 2021; Qiao et al., 2024), 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 research suggested that rule-based methods often failed to detect complex fault interactions due to their rigid thresholding mechanisms (Kordestani et al., 2019; Zhang et al., 2023). 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 (Chen & Li, 2017). The ability of LSTMs to model time-dependent fault progression further supports their growing adoption in real-time transformer monitoring applications. 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 (Zhang et al., 2023). 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 Qiao et al. (2024), 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 (Cervantes-Bobadilla et al., 2023). 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 (Cervantes-Bobadilla et al., 2023; Long 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 Zhang et al. (2023), 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 (Hao et al., 2020). 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.

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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 (Li et al., 2020), 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 Hao et al. (2020), 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 Ahmad et al. (2024), 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 (Du et al., 2024). 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 Ahmad et al., (2024), 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 (Kordestani et al., 2019). This suggests that addressing interpretability challenges is essential for increasing confidence in AI-based transformer monitoring solutions.

CONCLUSION

This systematic review highlights the significant advancements in transformer fault diagnosis achieved through the integration of artificial intelligence (AI) and machine learning (ML) techniques, particularly deep learning models, hybrid AI approaches, and predictive maintenance frameworks. The findings confirm that deep learning architectures such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks significantly improve fault detection accuracy, outperforming traditional diagnostic methods by automating feature extraction and enhancing real-time fault classification. Hybrid AI models, including artificial neural network (ANN) and support vector machine (SVM) combinations, further enhance diagnostic reliability by leveraging the strengths of multiple classifiers to optimize fault detection across diverse transformer datasets. AI-driven predictive maintenance models contribute to increased transformer reliability by enabling condition-based monitoring, reducing unplanned outages, and optimizing asset management strategies. Additionally, multi-sensor integration techniques, particularly wireless sensor networks (WSNs) and IoT-enabled monitoring, enhance fault detection accuracy by fusing data from different diagnostic modalities such as dissolved gas analysis (DGA) and partial discharge (PD) monitoring. However, the review also identifies challenges related to the interpretability of deep learning models, highlighting the need for explainable AI (XAI) techniques such as SHAP and LIME to bridge the gap between model accuracy and transparency in decision-making. The findings reinforce the growing importance of AI in transformer diagnostics, demonstrating that while accuracy improvements have been substantial, addressing model interpretability, data integration challenges, and real-world implementation barriers remains critical for the widespread adoption of AI-driven fault detection systems in power grid applications.

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