Integration of Machine Learning and AI for Fault Detection in Electrical Power Systems

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ABSTRACT

The integration of machine learning (ML) and artificial intelligence (AI) in electrical power system fault detection has revolutionized the field by enhancing diagnostic accuracy and operational resilience. Traditional protection systems, primarily based on rule-based relays, struggle with nonlinear behaviors and evolving grid structures. ML techniques such as decision trees, support vector machines, and deep learning have proven effective in improving fault detection and classification by analyzing complex power system data. However, challenges like class imbalance, model interpretability, and environmental uncertainties remain. Despite these obstacles, ML-based models represent a robust solution for intelligent, adaptive, and scalable fault detection in future smart grids.

Keywords: *Machine Learning, Fault Detection, Smart Grids, Power Systems, Artificial Intelligence.*

I. INTRODUCTION

Electrical power systems form the backbone of modern industrial, commercial, and residential infrastructure, ensuring continuous and reliable electricity supply. With the increasing complexity, interconnectivity, and scale of power grids, maintaining system stability and operational reliability has become more challenging than ever. Faults in electrical power systems—such as short circuits, open circuits, insulation failures, line-to-line faults, and equipment malfunctions—can lead to severe consequences including power outages, equipment damage, economic losses, and safety hazards. Traditional protection systems, which rely primarily on rule-based relays and threshold mechanisms, have been widely used for fault detection and isolation. However, these conventional approaches often struggle in handling nonlinear system behavior, noisy signal environments, and rapidly changing operating conditions. Moreover, they lack adaptability to evolving grid structures, distributed generation systems, and smart grid environments. As a result, there has been a significant shift toward intelligent and data-driven approaches for fault detection and classification in modern power systems. In this context, machine learning (ML) and artificial intelligence (AI) have emerged as transformative technologies capable of improving diagnostic accuracy, reducing response time, and enhancing system resilience under uncertain and dynamic operating conditions (Aziz et al., 2024; Samson et al., 2024).

The integration of machine learning techniques into electrical power system fault analysis has gained substantial attention due to their ability to learn complex patterns from historical and real-time data. Unlike conventional methods that depend on predefined mathematical models, ML-based approaches extract hidden features from voltage, current, frequency, and waveform data to identify abnormal conditions with higher precision. Various algorithms such as decision trees, support vector machines (SVM), k-nearest neighbors (KNN), random forests, artificial neural networks (ANN), convolutional neural networks (CNN), and deep autoencoders have been successfully applied for fault detection and classification tasks. For instance, Vivek et al. (2024) demonstrated that decision tree and random forest models, combined with preprocessing techniques like SMOTE, significantly improve classification accuracy in electrical fault datasets. Similarly, Ilius et al. (2023) showed that SVM-based models are capable of predicting fault conditions using system state variables such as bus voltages and generator angles. Deep learning techniques, in particular, have shown exceptional performance in capturing nonlinear relationships in power system data. Yoon and Yoon (2022) developed a CNN-based framework for power quality disturbance classification, achieving more than 99% accuracy, highlighting the strength of deep architectures in waveform-based fault diagnosis. Additionally, Nayak et al. (2026) introduced convolutional autoencoders for anomaly detection, demonstrating their effectiveness in reducing dimensionality and improving computational efficiency while maintaining high accuracy. These studies collectively indicate that ML-based models provide a robust alternative to traditional protection schemes by offering improved adaptability, scalability, and predictive capabilities in complex electrical environments.

Despite significant advancements, several challenges persist in the development and deployment of machine learning-based fault detection systems in electrical power networks. One of the primary issues is the availability of high-quality labeled datasets, as real-world fault events are rare, unpredictable, and often imbalanced. Kabir (2026) emphasized that power system datasets typically contain a dominant proportion of normal operating conditions compared to fault states, leading to class imbalance problems that can affect model performance. Another challenge lies in ensuring model interpretability and reliability, particularly in safety-critical applications such as transmission line protection and industrial power systems. While deep learning models offer high accuracy, they are often considered “black-box” systems, making it difficult to interpret decision-making processes. Furthermore, variations in operating conditions, environmental factors, and system configurations introduce uncertainties that may reduce model generalization capability. Rezaee et al. (2026) highlighted similar concerns in nanosatellite power systems, where environmental disturbances and system constraints significantly affect fault behavior. To address these challenges, researchers are increasingly focusing on hybrid models, feature engineering techniques, transfer learning, and explainable AI (XAI) frameworks to enhance transparency and robustness. Additionally, big data analytics and distributed computing frameworks, such as knowledge graphs proposed by Zhou et al. (2022), are being explored to improve real-time fault diagnosis in large-scale power systems. Therefore, the growing integration of machine learning with power system protection represents a significant paradigm shift toward intelligent, adaptive, and self-learning electrical networks capable of ensuring higher reliability and operational efficiency in future smart grid infrastructures (Alabbawi et al., 2023; Sundararaman & Jain, 2023).

II. RESEARCH BACKGROUND

Rezaee et al., (2026) investigated a novel approach for detecting faults in Nanosatellites' electrical power systems operating in Low Earth Orbit (LEO) without an Attitude Determination and Control Subsystem (ADCS). They highlighted that each component of such systems was susceptible to faults due to environmental conditions, launcher pressure, and pressure tolerance limitations. The study identified common faults, including line-to-line faults and open circuits in the photovoltaic subsystem, short circuits and open circuits in IGBTs of the DC–DC converter, and regulator faults in the ground battery. The system was initially simulated under fault-free conditions using a neural network, which employed solar radiation and solar panel surface temperature as inputs and current and load as outputs. Subsequently, different faults were diagnosed by classifying patterns and fault types through the neural network classifier. The study also compared alternative machine learning techniques for fault classification, including PCA-based classification, decision trees, and k-nearest neighbors (KNN), demonstrating their potential for accurate fault detection.

Nayak et al., (2026) highlighted that fault detection in electrical power systems had recently drawn significant attention from both academic and industrial researchers. They observed that, despite numerous fault detection methods developed over the past decade, practical implementation remained challenging due to the probabilistic nature of fault occurrences and system parameters. It was noted that protective systems were responsible for detecting, classifying, and localizing faulty voltage and current magnitudes, ultimately triggering circuit breakers to isolate affected lines. The authors emphasized the critical role of obtaining reliable training and testing data, which was often limited. They suggested that deep learning techniques, particularly pattern classifiers capable of learning, generalization, and parallel processing, offered promising solutions for intelligent fault detection. To address these challenges, they proposed an anomaly-based approach using deep autoencoders, employing Convolutional Autoencoders (CAE) for dimensionality reduction to reduce training time. Their method was reported to outperform alternative approaches, achieving accuracies of 97.62% and 99.92% on simulated and publicly available datasets.

Kabir (2026) was reported to have investigated intelligent condition monitoring and fault diagnosis of electrical power and control systems using machine learning–based predictive analytics to assess diagnostic reliability, robustness across operating regimes, and explanatory value under realistic data conditions. The study was said to have analyzed a large multi-asset dataset comprising 211,200 time-window observations from electrical, thermal, mechanical, insulation-related, and control-residual measurements, including 312 documented fault events. Descriptive analysis reportedly revealed a pronounced class imbalance, with healthy operations constituting 88.2% of observations, degraded states 7.1%, and fault states 4.7%, and fault behavior occurring in temporally clustered events with a median duration of 18 minutes. Correlation and collinearity analyses were noted to indicate moderate within-domain feature dependence but low cross-domain redundancy, supporting multivariate modeling. Reliability assessments were observed to demonstrate acceptable to strong internal consistency across indicator domains and high temporal stability under stable operating regimes. Multivariate regression and hypothesis testing were reported to show that multi-domain predictive models explained substantially more variance in fault outcomes than baseline models, with statistically significant and practically meaningful improvements in diagnostic performance. Prognostic-oriented analyses were said to indicate systematic risk escalation prior to documented intervention events. Overall, the findings were interpreted as providing quantitative evidence that regime-aware, multi-domain machine learning–based analytics enhanced fault detection reliability, mitigated confounding from operating variability, and supported interpretable diagnostic inference in electrical power and control systems.

Vivek et al. (2024, April) highlighted that electrical faults had posed significant challenges in power systems, often resulting in operational disruptions and safety concerns. They emphasized that timely detection and localization of such faults were critical for maintaining uninterrupted power supply and preventing hazards. In this regard, they reported that machine learning techniques had emerged as promising tools to enhance fault diagnosis systems. The study presented a comprehensive methodology for electrical fault detection and localization, drawing inspiration from real-world scenarios like power grid failures and industrial equipment malfunctions. The authors focused on decision tree classifiers and compared their performance with random forest algorithms. They described preprocessing procedures, including feature engineering and normalization, and addressed class imbalance by employing the Synthetic Minority Over-sampling Technique (SMOTE) to improve robustness. Using a diverse dataset of fault types, they conducted extensive experiments, demonstrating the superiority of decision tree-based approaches in achieving high accuracy. Their findings were suggested to provide practical insights for real-world implementation in power systems and industrial settings.

Aziz et al. (2024) emphasized that electricity, being essential to modern society, required a consistent and uninterrupted supply, and that faults in power systems posed significant challenges, underlining the importance of effective fault identification and diagnosis. They reviewed artificial intelligence (AI)-based methods for fault detection and diagnosis, with a particular focus on deep learning approaches. Their work compared various studies to provide an accessible introduction for readers unfamiliar with the field while also exploring advanced applications, such as UV-visible video processing for detecting incipient faults by analyzing corona discharge and air ionization. The study highlighted the growing role of deep learning in monitoring early-stage faults and noted that, despite ongoing research, the field still lacked a structured framework, indicating the necessity for continued advancement in applying AI for efficient and reliable fault detection in power systems.

Samson et al., (2024, April) reviewed the challenges associated with detecting and locating faults in electrical grids, noting that such faults often led to energy loss, reduced revenue, and equipment damage. They examined the historical evolution of fault detection methods in power systems, emphasizing the limitations of traditional approaches. The study analyzed the integration and application of machine learning algorithms to enhance fault identification processes, illustrating how these techniques improved detection accuracy and efficiency. The authors highlighted the critical role of machine learning in preventing faults, conserving energy, and strengthening the resilience of power infrastructure, thereby presenting it as a transformative tool in modern power systems engineering.

Sundararaman and Jain (2023) investigated the disruption of balanced operating power systems, where all elements carried normal currents and bus voltages remained within prescribed limits, due to faults occurring within the system. They highlighted that overhead transmission networks were particularly vulnerable to atmospheric disturbances, leading to the highest statistical probability of faults. They emphasized that quick and accurate fault detection facilitated timely remedial actions, offering significant economic and operational benefits, and that maintaining continuous supply functionality was critical for reliable system operation. The study underscored the importance of identifying and locating faults to prevent cascading failures. They noted that fast electromagnetic transients in current and voltage waveforms during faults could provide valuable insights into abnormal operating conditions. To analyze these non-stationary signals, they applied wavelet transform (WT) techniques, which offered variable window sizes and improved time–frequency resolution. WT-based intelligent techniques were employed to detect and classify faults by examining the maximum detail coefficients of phase currents using Daubechies 4 (db4) wavelets. Extensive simulations on the standard IEEE 5-Bus system demonstrated the method's effectiveness in accurate fault detection, enabling timely protective actions.

Ilius et al., (2023) investigated the application of machine learning techniques for monitoring the health and detecting faults in various power system components, such as transformers, generators, and induction motors. They highlighted that fault monitoring was conventionally carried out using predetermined datasets representing healthy and faulty system conditions. The study aimed to identify the onset of system faults through a Support Vector Machine (SVM) approach, which was employed to anticipate power system instability before it reached critical levels. Bus voltages, generator angles, and the corresponding pre- and post-fault times were utilized as training data for the SVM to recognize abnormal conditions. The authors reported that, once trained, the SVM could determine the fault status by analyzing new test data after disturbances, thereby demonstrating its effectiveness for early fault detection and system health monitoring.

Alabbawi et al. (2023) proposed an intelligent protection relay design employing artificial neural networks to safeguard electrical components in power systems against various faults. They focused on protecting transformers and transmission lines through intelligent differential and distance relays, respectively. Faults were categorized, and their locations were identified using three-phase current values and zero-sequence current characteristics to distinguish between earth and non-earth faults. The study selected optimal parameters for the neural network to achieve minimal error, establishing the Levenberg–Marquardt algorithm as the most effective training method for the differential relay-based system. Fault detection and classification were carried out using 20 and 50 hidden layers, yielding error rates of 9.9873×10^{-3} and 1.1953×10^{-29}, respectively. For the distance relay, hidden layer neuron counts of 400, 250, and 300 were applied for fault detection, classification, and location, resulting in training errors of 7.8761×10^{-2}, 1.2063×10^{-6}, and 1.1616×10^{-26}, demonstrating the high accuracy and efficiency of the proposed intelligent relay system.

Zhou et al. (2022) investigated fault detection in electric power systems, emphasizing its critical role in daily maintenance. They noted that big data and knowledge graph (KG) techniques had been increasingly applied in the industrial Internet of Things and held significant potential for enhancing fault detection performance. The study analyzed a distributed KG framework in which multiple devices trained local detection models using historical fault data and current device states, assisted by a central server. It was highlighted that devices interacted within the KG framework to perform regional computation and model aggregation under specified latency constraints, aiming to improve detection accuracy. The research further described enhancements to the KG framework by selecting an optimal set of active devices while controlling latency and data transmission. Two data transmission frequency allocation schemes were proposed: one relying on instantaneous device state information and another employing particle swarm optimization with statistical device states. Simulation results reportedly demonstrated the framework's superior performance and convergence in fault detection.

Yoon and Yoon (2022) investigated the robust and efficient diagnosis of power quality disturbances (PQDs) in electric power systems (EPSs), emphasizing its importance for protecting power systems with minimal damage. They noted that conventional fault detection methods in EPSs primarily relied on heavy mathematical calculations, which often caused delayed responses to PQDs. To address these limitations, they explored deep learning as a diagnostic approach, highlighting its capability to extract features from large datasets and capture subtle differences in electrical waveforms under faulty conditions. In their study, they proposed a convolutional neural network (CNN)-based method using simulated three-phase voltage and current waveforms generated from PSCAD/EMTDC software. The research assessed various PQDs to demonstrate the method's applicability for fault diagnosis. The CNN model, trained through end-to-end supervised learning, was reported to classify both the type and location of faults successfully. Additionally, they observed that data simulated at a 50 Hz sampling rate also enabled accurate fault detection, achieving over 99% accuracy, suggesting potential practical utility.

III. KEY FINDINGS FROM STUDY

Author	Year	Objective	Methodology	Key Findings	Limitations
Rezaee et al.	2026	Fault detection in nanosatellite power systems	Neural network, PCA, KNN	Neural networks effectively classified faults like short circuits and open circuits with high accuracy	Limited to simulated nanosatellite environment
Nayak et al.	2026	Improve fault detection using anomaly detection	Convolutional autoencoder (CAE)	Achieved up to 99.92% accuracy; reduced dimensionality and training time	Requires large labeled datasets for training stability

Kabir	2026	Condition monitoring of power systems	Multi-domain ML predictive analytics	Multi-feature models improved fault prediction and reliability	Class imbalance in dataset affected distribution of fault classes
Vivek et al.	2024	Fault detection and localization	Decision tree, random forest, SMOTE	Decision tree models achieved high accuracy and robustness in classification	Limited generalization to real-time systems
Aziz et al.	2024	Review of AI in fault diagnosis	Literature-based review of deep learning methods	Highlighted importance of deep learning for early fault detection	Lack of unified AI framework for power systems
Samson et al.	2024	ML applications in power system fault detection	Systematic review of ML models	ML improves detection accuracy and grid resilience	Practical implementation challenges remain
Sundararaman & Jain	2023	Fault classification in transmission systems	Wavelet transform (db4)	Accurate classification using time-frequency analysis	Computationally intensive for real-time use
Ilius et al.	2023	Early fault detection in power systems	Support Vector Machine (SVM)	SVM successfully detected instability using system state data	Requires high-quality labeled datasets
Alabbawi et al.	2023	Intelligent protection relay design	Artificial Neural Networks (ANN)	Achieved very low error rates in fault detection and classification	High model complexity and training cost
Zhou et al.	2022	Distributed fault diagnosis system	Big data + knowledge graph + ML	Improved fault detection efficiency using distributed learning	Dependence on communication latency constraints
Yoon & Yoon	2022	Power quality disturbance diagnosis	Convolutional Neural Network (CNN)	Achieved >99% accuracy in fault classification	Requires high computational resources

IV. CONCLUSION

The review of existing literature on machine learning-based fault detection and classification in electrical power systems clearly demonstrates a significant transformation from traditional protection methods toward intelligent, data-driven diagnostic frameworks. Conventional techniques, although reliable for simple and well-defined fault conditions, are often limited in handling the complexity, uncertainty, and dynamic behavior of modern power grids. In contrast, machine learning and deep learning approaches have shown remarkable capability in improving fault detection accuracy, reducing response time, and enhancing system adaptability under varying operational conditions. Studies such as those by Yoon and Yoon (2022) and Nayak et al. (2026) have highlighted the exceptional performance of convolutional neural networks and autoencoder-based models in identifying and classifying faults with accuracies exceeding 99%, demonstrating the effectiveness of deep architectures in handling nonlinear electrical signals. Similarly, approaches using decision trees, support vector machines, and random forests have proven valuable for interpretable and efficient fault classification, particularly in real-world industrial applications (Vivek et al., 2024; Ilius et al., 2023). Furthermore, hybrid and multi-domain approaches, as discussed by Kabir (2026), indicate that integrating electrical, thermal, and mechanical data significantly enhances predictive reliability and system robustness. However, despite these advancements, challenges such as data imbalance, limited availability of labeled fault datasets, computational complexity, and lack of model interpretability continue to restrict large-scale deployment in practical systems. Additionally, environmental variability and system heterogeneity further complicate model generalization across different grid conditions. Overall, the literature confirms that machine learning-based fault detection systems represent a highly promising direction for future smart grids, enabling faster, more accurate, and more reliable fault diagnosis. Continued research focusing on explainable AI, real-time implementation, and hybrid modeling approaches will be essential to bridge the gap between theoretical developments and practical deployment in next-generation electrical power systems (Aziz et al., 2024; Samson et al., 2024).

V. FUTURE SCOPE

The future of machine learning-based fault detection and classification in electrical power systems is highly promising, particularly with the rapid evolution of smart grids, renewable energy integration, and Industry 4.0 technologies. One of the most significant future directions is the development of real-time, adaptive fault detection systems capable of operating efficiently in highly dynamic and decentralized power networks. As modern grids increasingly incorporate distributed energy resources such as solar, wind, and electric vehicles, there will be a growing need for intelligent algorithms that can handle highly variable and nonlinear system behavior. In this context, advanced deep learning architectures such as transformer models, graph neural networks (GNNs), and reinforcement learning-based diagnostic systems are expected to play a key role in improving fault prediction accuracy and system responsiveness. Another important area of future research is explainable artificial intelligence (XAI), which aims to make machine learning models more transparent and interpretable for power system engineers. This is particularly critical in safety-sensitive applications where understanding the reasoning behind a fault classification decision is essential. Additionally, hybrid modeling approaches that combine physics-based electrical models with data-driven machine learning techniques are expected to enhance both accuracy and generalization capability across different operating conditions. Edge computing and Internet of Things (IoT)-based architectures will further enable distributed fault detection at the device level, reducing latency and improving real-time decision-making in large-scale power networks. Moreover, the integration of big data analytics and cloud computing will allow continuous learning from vast amounts of operational data, improving predictive maintenance strategies and reducing system downtime. Future research is also likely to focus on addressing challenges such as data imbalance, cybersecurity threats, and model robustness under adversarial conditions. Overall, the convergence of AI, IoT, and smart grid technologies will drive the next generation of intelligent fault diagnosis systems, ensuring higher reliability, efficiency, and sustainability of electrical power systems (Nayak et al., 2026; Zhou et al., 2022).

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