Intelligent Machine Learning Framework for Accurate Fault Detection and Classification in Modern Electrical Power Systems

Suraj Raghav
M. Tech. in Electrical Engineering, CBS Group of Institutions, Jhajjar, Haryana.

Nisar
A.P Electrical Department, CBS Group of Institutions, Jhajjar, Haryana.

ABSTRACT

This study focuses on machine learning-based fault detection and classification in electrical power systems. Power system faults such as line-to-ground, line-to-line, double-line-to-ground, and three-phase faults can disturb stability, damage equipment, and interrupt electricity supply. Machine learning techniques analyze voltage, current, frequency, and transient signal features to identify and classify faults accurately. Algorithms such as Decision Tree, Support Vector Machine, Random Forest, K-Nearest Neighbour, and Artificial Neural Network were considered for comparative evaluation. The study shows that machine learning improves fault detection accuracy, reduces response time, and supports reliable smart grid protection.

Keywords: *Machine Learning, Fault Detection, Fault Classification, Electrical Power System.*

I. INTRODUCTION

Machine learning-based fault detection and classification in electrical power systems has emerged as an important research area because modern power networks are becoming increasingly complex, interconnected, automated, and dependent on continuous supply reliability. Electrical power systems consist of generation units, transmission lines, transformers, substations, distribution feeders, circuit breakers, protective relays, sensors, and loads that work together to deliver electrical energy safely and efficiently to domestic, commercial, industrial, and agricultural consumers. However, during operation, these systems are exposed to different abnormal conditions such as short-circuit faults, line-to-ground faults, line-to-line faults, double-line-to-ground faults, three-phase faults, transformer winding faults, insulation failures, overloads, voltage instability, frequency deviations, switching transients, lightning strikes, equipment ageing, and environmental disturbances. Such faults may occur suddenly and can disturb the normal flow of current and voltage, damage expensive equipment, reduce power quality, create safety hazards, and interrupt the supply of electricity over a wide area. Therefore, accurate and rapid fault detection and classification are essential for maintaining system stability, minimizing outage duration, protecting equipment, and improving the overall reliability of power delivery. In traditional power systems, fault detection and classification have mainly depended on protection relays, impedance-based methods, differential protection, overcurrent protection, distance relays, travelling wave techniques, and threshold-based decision-making systems. These conventional methods are useful and widely applied, but they may face limitations under changing system conditions, high fault resistance, nonlinear loads, distributed generation, renewable energy integration, power electronic converters, noisy measurements, and complex transient behaviour. With the growth of smart grids, microgrids, renewable energy sources, and digital monitoring systems, the amount of data generated from phasor measurement units, intelligent electronic devices, smart meters, supervisory control and data acquisition systems, and digital fault recorders has increased significantly. This large volume of operational data creates an opportunity to apply machine learning techniques for intelligent fault diagnosis. Machine learning is a branch of artificial intelligence that enables computer systems to learn patterns from data and make decisions without being explicitly programmed for every condition. In the context of electrical power systems, machine learning models can be trained using voltage, current, frequency, phase angle, impedance, active power, reactive power, harmonic components, and transient signal features obtained from real-time measurements or simulation-based datasets. After training, these models can detect whether a fault has occurred, classify the fault type, identify the faulty phase, estimate fault location, and sometimes predict fault severity. Common machine learning algorithms used in this field include Support Vector Machine, Decision Tree, Random Forest, K-Nearest Neighbour, Naive Bayes, Artificial Neural Network, Convolutional Neural Network, Recurrent Neural Network, Long Short-Term Memory network, Extreme Learning Machine, Gradient Boosting, and hybrid intelligent models. Each algorithm has its own advantages: decision trees are simple and interpretable, random forests provide strong classification accuracy, support vector machines perform well with limited data, neural networks capture nonlinear relationships, and deep learning models can automatically extract hidden features from complex electrical signals. The effectiveness of machine learning-based fault detection depends on the quality of data, feature selection, preprocessing techniques, model training, validation, and testing. Signal processing techniques such as Fast Fourier Transform, Wavelet Transform, Stockwell Transform, Park's Transformation, Principal Component Analysis, and statistical feature extraction are often used to convert raw electrical signals into meaningful inputs for the learning model. For example, during a line-to-ground fault, the current in the faulty phase may increase sharply while voltage drops significantly; during a line-to-line fault, two phases show abnormal current behaviour; and during a three-phase fault, all phases are affected simultaneously. Machine learning models learn such patterns and classify them more efficiently than fixed-rule systems in many cases. Another major advantage of machine learning is adaptability. Power systems are no longer purely centralized; they now include solar photovoltaic systems, wind farms, battery energy storage, electric vehicles, and flexible loads. These elements introduce bidirectional power flow, variable generation, and unpredictable operating conditions. Conventional protection settings may not always respond correctly in such dynamic environments, whereas data-driven models can be retrained or updated using new operational data to improve their performance. Machine learning also supports real-time monitoring and automation, which are important for smart grid protection and self-healing power networks. A self-healing grid requires fast fault identification, automatic isolation of faulty sections, and restoration of healthy parts of the network. Intelligent classification helps control centres and protection devices take quick decisions by distinguishing between temporary disturbances and permanent faults. In addition, machine learning-based systems can reduce human error, assist engineers in fault analysis, improve maintenance planning, and support predictive maintenance by identifying early signs of equipment failure before a major fault occurs. Despite these benefits, the implementation of machine learning in power system protection also involves several challenges. The model requires reliable and diverse datasets that include different fault types, fault locations, loading conditions, fault resistances, system configurations, and noise levels. In many real power systems, actual fault data are limited because severe faults do not occur frequently, and collecting labelled data can be difficult. Therefore, researchers often use simulation platforms such as MATLAB/Simulink, PSCAD, ETAP, DigSILENT PowerFactory, or real-time digital simulators to generate training data. Another challenge is model generalization, because a model trained on one system may not perform accurately on another system with different parameters. Cybersecurity, communication delay, sensor errors, interpretability, computational burden, and real-time implementation are also important issues that must be addressed before deploying machine learning models in critical power infrastructure. Furthermore, protection systems require very high dependability and security because a wrong decision may either fail to isolate a fault or unnecessarily disconnect healthy parts of the network. Therefore, machine learning models must be carefully tested, validated, and integrated with conventional protection schemes rather than replacing them blindly. The combination of domain knowledge from power engineering and intelligent learning algorithms can produce more robust and practical fault diagnosis systems. In recent research, hybrid approaches have become popular, where signal processing, optimization algorithms, and machine learning classifiers are combined to improve accuracy and speed. For example, wavelet-based feature extraction may be combined with neural networks, or optimization techniques such as Particle Swarm Optimization, Genetic Algorithm, and Grey Wolf Optimization may be used to select the best features or tune model parameters. Deep learning-based techniques are also gaining attention because they can process raw waveform data and learn complex temporal and spatial patterns automatically. Such models are particularly useful for high-dimensional data from smart grid sensors. Overall, machine learning-based fault detection and classification represents a significant advancement in electrical power system protection. It provides a faster, more accurate, flexible, and intelligent approach to identify faults and support decision-making in modern power networks. As power systems continue to evolve toward digitalization, renewable energy integration, and automation, intelligent fault diagnosis will play a crucial role in ensuring reliable, safe, and efficient power supply. The study of this topic is therefore highly relevant because it connects electrical engineering, data science, artificial intelligence, and smart grid technology to solve real-world problems related to power system reliability and protection.

II. RESEARCH BACKGROUND

Antony et al. (2026) investigated an intelligent battery safety framework that aimed to enhance fault detection and risk management compared to conventional static monitoring systems. They developed a method that integrated redundant multi-modal sensing with a Convolutional Autoencoder (CAE) and employed a Transformer-based anomaly classifier to capture spatial and temporal dependencies in the sensing data for fault prediction. The study reported the implementation of Bayesian sensor fusion to correct redundant measurements and the application of fuzzy logic reasoning to convert anomaly scores into risk-based safety actions, supporting interpretable decision-making. The State of Health (SoH) of the battery was estimated through real-time fusion of thermal profiles, routing voltage, and cycle aging data, which enabled accurate tracing of degradation trends during faults. Validation experiments using MATLAB/Simulink and real-time hardware-in-the-loop fault injection demonstrated a 15 % reduction in false positives, fault detection accuracy up to 98 %, and reliable actuation within 20 ms. The findings were highlighted as a proof of concept for the CAE-Transformer-Fuzzy hybrid framework as an effective approach for adaptive battery management in dynamic, safety-critical applications.

Hossain et al., (2026) investigated the increasing complexity and dynamic nature of modern electrical grids, emphasizing the necessity for advanced and adaptive fault diagnosis systems to maintain reliability and minimize downtime. They proposed a novel adaptive fault detection and localization approach for three-phase transmission lines based on a Long Short-Term Memory (LSTM) Autoencoder. The model was designed to operate in an unsupervised manner, learning standard operational patterns from three-phase voltage and current signals and identifying faults as anomalies via high reconstruction errors. The study reported that the method was trained and tested on a comprehensive dataset of over 50,000 simulated fault events generated in MATLAB/Simulink and further validated on 1,000 real-world fault instances from an open-source repository. The results indicated exceptional performance, with 98 % accuracy, a 2 % false positive rate, and over 15 % improvement in F1-score compared to traditional methods such as DFT and Wavelet, as well as other deep learning benchmarks including standard LSTM and 1D-CNN. The model was noted to exhibit resilience to noise, maintaining an F1-score above 92 % at 20 dB SNR, and computational efficiency suitable for real-time deployment, demonstrating its potential significance for enhancing adaptive fault management and monitoring in modern power systems.

Tian et al. (2026) investigated the challenges of detecting series arc faults (SAFs), recognized as a major hidden cause of electrical fires, in household multi-load circuits where faulty branch signals were often obscured by power frequency and integer harmonic components from normal branches. They proposed a feature enhancement approach combining seasonal trend decomposition with recursive least squares adaptive filtering (STD-RLS) and developed a novel SAF detection and line selection method integrating variational mode decomposition (VMD) with a support vector machine (SVM) recognition model. SAFs were first simulated across varying branch numbers, load types, and fault locations. The STD-RLS method was then applied to remove power frequency and harmonic interference, facilitating extraction of fault features. These signals were processed via VMD to derive waveform variability coefficients, time-domain peaks, frequency-domain peaks, and spectral energy for each intrinsic modal function. Finally, an SVM-based recognition model was constructed for fault detection and line selection, and the results demonstrated that the proposed method substantially enhanced fault features, achieving detection and line selection accuracies exceeding 97%.

Ibrahim et al. (2024) conducted a comprehensive review on incipient fault detection methodologies in power distribution networks, emphasizing the significance of early fault detection for system reliability and stability. They highlighted that incipient faults, being subtle and difficult to identify, posed substantial risks to uninterrupted power service and could lead to catastrophic failures if unaddressed. The review initially outlined the fundamental concepts of incipient faults and their impacts on distribution systems. It subsequently surveyed detection methods, distinguishing between conventional rule-based approaches and advanced data-driven techniques, including machine learning and artificial intelligence. Each category was analyzed with respect to its operational principles, advantages, and limitations. The authors also identified key challenges and emerging trends, such as the integration of smart grid technologies, the application of big data analytics, and the development of hybrid detection strategies. Overall, the study provided critical insights for both practitioners and researchers seeking to enhance network reliability and advance fault detection technologies.

Akhtar et al. (2024) investigated the critical importance of reliable operation in electrical power transmission systems, emphasizing that faults could cause substantial disruptions, economic losses, and safety hazards. They highlighted the necessity of protective strategies to safeguard transmission lines from faults due to natural disturbances, short circuits, and open-circuit conditions. The study employed an advanced artificial neural network (ANN) methodology to detect and classify faults, differentiating between single-phase, three-phase, and three-phase symmetrical faults. Fault data were generated using line currents and voltages under varied conditions, modeled in MATLAB, and analyzed via time-series signal data. To address dataset imbalance, SMOTE-based oversampling was applied. Four machine-learning models and one deep-learning model were developed, alongside a novel Explainable Boosting (EB) method combining boosting techniques with interpretable tree models. Simulation results reportedly demonstrated detection accuracies up to 99%, validated through hyperparameter optimization, k-fold cross-validation, and eXplainable AI analyses. The study concluded that the proposed approach offered a scalable, interpretable, and efficient framework for smart grid fault detection.

Kumar et al., (2024, May) highlighted that multiple uncontrollable factors could contribute to unexpected failures in electrical power networks, emphasizing the critical need to prevent such disturbances from affecting other protective system components. They noted that protective systems were tasked with identifying and classifying potentially hazardous voltage or current lines, while circuit breakers were triggered via protection relays to isolate malfunctioning lines. The study introduced an SVM-CNN architecture for detecting outages in transmission lines, stressing that the correct sequence of preprocessing, feature selection, and model training was vital. It was observed that data preprocessing was essential for anomaly-based fault detection algorithms to accurately capture and interpret system behavior, and feature selection was found to reduce data volume while focusing detection on the most relevant characteristics. The implementation of this approach reportedly led to significant improvements in detection performance, with accuracy reaching up to 95.70%.

Thomas et al. (2023) investigated fault detection and localization in electrical power lines, emphasizing its longstanding importance for ensuring uninterrupted network operation and preventing equipment damage. They highlighted that neglected faults could lead to significant power loss and economic repercussions, underscoring the need for efficient detection mechanisms. Their study introduced an end-to-end deep learning approach to identify and locate symmetrical, unsymmetrical, and high-impedance faults (HIFs) within a distribution system. Specifically, they proposed a novel deep convolutional neural network (CNN) transformer model, wherein 1-D CNNs were employed for feature extraction and a transformer encoder was utilized for sequence learning. The attention mechanism of the transformer encoder was applied to integrate sequence embeddings, focusing on critical time steps to capture long-term dependencies in temporal current data. Fault scenarios were simulated in MATLAB Simulink using the IEEE 14-bus distribution system, and the model's performance, evaluated with F1-score, Matthews correlation coefficient (MCC), and accuracy, was reported to surpass conventional fault-detection techniques, particularly in predicting HIFs.

Shakiba et al. (2023) examined the increasing demands of modern power systems and smart grids, highlighting the necessity for advanced fault diagnosis techniques to prevent unexpected interruptions and financial losses. They emphasized that transmission lines represent a critical component of such systems and that faster, more accurate fault identification tools were essential to ensure reliable and resilient electrical power delivery. The study reviewed recent machine learning–based methods employed for fault detection, classification, and location estimation, noting that the high costs associated with potential faults necessitated immediate diagnostic interventions. Various algorithms were surveyed, including naive Bayesian classifiers, decision trees, random forests, k-nearest neighbors, and support vector machines, alongside artificial neural network models such as feedforward networks, convolutional networks, and adaptive neuro-fuzzy inference systems. The authors concluded that these intelligent approaches had demonstrated significant promise in enhancing the speed and accuracy of fault management in transmission line systems.

Thomas and Shihabudheen (2023) proposed a study in which a neural architecture search algorithm was employed to obtain an optimal Transformer model for detecting and localizing various power system faults and uncertain conditions, including symmetrical and unsymmetrical shunt faults, high-impedance faults, switching events, insulator leakage, and transformer inrush current in distribution systems. They argued that the Transformer model addressed the high memory consumption associated with deep CNN attention models and the long-term dependency limitations of RNN attention models. The study highlighted the inefficiency of manually designing attention mechanisms and feedforward layers, and therefore applied the Differential Architecture Search (DARTS) algorithm to automatically generate optimal Transformer architectures with reduced search time, treating the network search as an end-to-end differentiable problem. The model was tested on the IEEE 14-bus system and the VSB power line fault detection database, achieving high performance metrics, including F1-Score, Matthews Correlation Coefficient, accuracy, and AUC. Additionally, they examined the architecture's transferability using real-world power line data for fault detection.

Maduako et al. (2022) highlighted that component fault detection and inventory had constituted one of the most significant bottlenecks for electricity transmission and distribution utilities, particularly in developing countries, in ensuring efficient service delivery and proper asset management for network optimization and load forecasting. They noted that, due to limitations in technology and data, security issues, the complexity of traditional methods, untimeliness, and high human costs, monitoring and managing electricity assets had remained a persistent challenge. In response, they investigated the use of oblique UAV imagery with high spatial resolution combined with fine-tuned deep Convolutional Neural Networks (CNNs) for automatic inspection and inventory of faulty components in electric power transmission networks. Their study assessed the performance of the Single Shot Multibox Detector (SSD) model in localizing, detecting, and classifying faults, proposing a CNN based on a multiscale feature pyramid network (FPN) that used aerial image patches and ground truth to detect faults in a single-phase procedure. They reported that the SSD ResNet50 variation achieved the highest mean Average Precision (mAP) of 89.61%, while all SSD-based models exhibited high precision, moderate recall, and balanced F1-scores. The authors concluded that combining UAV imagery with computer vision offered a cost-effective and timely approach to electricity asset monitoring, and they provided guidance on selecting deep learning architectures, ensuring adequate training samples, applying data augmentation, and managing intra-class heterogeneity.

Elmasry and Wadi (2022) investigated the challenges posed by the rising global demand for electrical power, highlighting that stable and reliable power grids were essential yet frequently hindered by fault occurrences. They noted that although numerous studies had aimed to detect electrical faults, many of these approaches suffered from limitations related to validation and automation. The authors proposed an electrical fault detection system grounded in anomaly detection, which was designed to overcome the shortcomings of existing methods and to be compatible with real-world power grids. They emphasized that the system incorporated two critical stages prior to training: data preprocessing, intended to prepare raw signals for modeling, and pre-training, aimed at optimizing model hyperparameters using the particle swarm optimization technique. Furthermore, One-Class Support Vector Machines and principal component analysis were employed as anomaly detection models to validate the system, while real-time data from the VSB dataset were used for training and testing. Their findings indicated that the proposed approach improved the performance of electrical fault detection compared to existing systems.

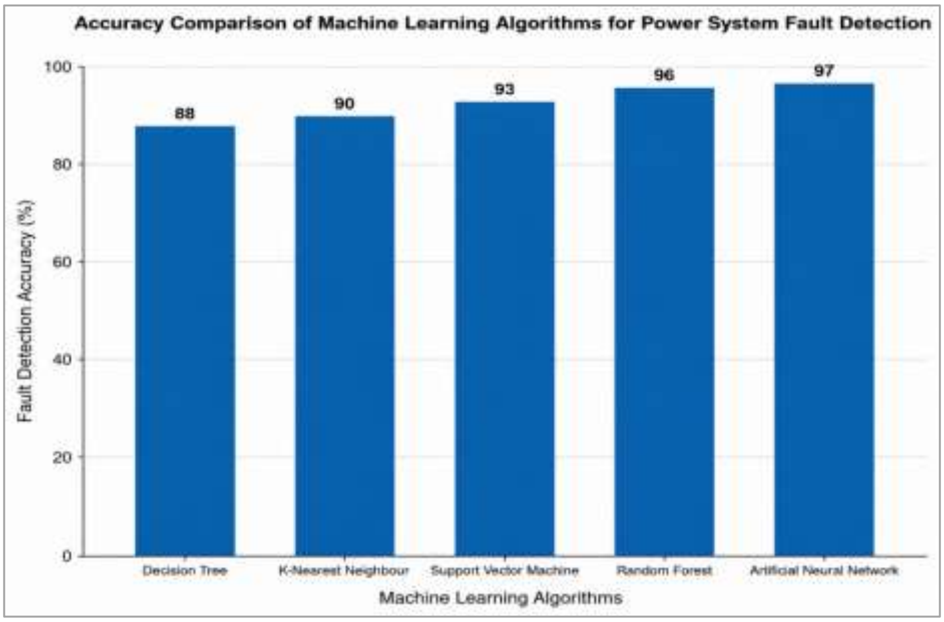
III. METHODOLOGY

The methodology of this study was based on the development of a machine learning model for accurate fault detection and classification in electrical power systems. First, a standard power system network was considered, including transmission lines, buses, sources, loads, and protection points. Different types of faults, such as single line-to-ground fault, line-to-line fault, double line-to-ground fault, and three-phase fault, were generated under varying operating conditions. The required electrical signals, mainly voltage, current, frequency, phase angle, active power, and reactive power, were collected from the system during both normal and faulty conditions. After data collection, preprocessing was performed to remove noise, missing values, and unnecessary signal variations. The collected signals were then normalized to maintain uniform data scale. Important features were extracted from voltage and current waveforms using statistical and signal-based parameters such as peak value, RMS value, mean, standard deviation, harmonic components, and transient variations. These extracted features were used as input variables for machine learning classification. The dataset was divided into training and testing sets. Several machine learning algorithms, including Decision Tree, K-Nearest Neighbour, Support Vector Machine, Random Forest, and Artificial Neural Network, were trained using the labelled fault data. Each model learned the relationship between input signal features and corresponding fault classes. After training, the models were tested using unseen data to evaluate their performance. Model performance was assessed using accuracy, precision, recall, F1-score, and fault detection time. The results obtained from different algorithms were compared to identify the most effective classifier. The final analysis focused on determining which machine learning technique provided higher accuracy, faster detection, and better reliability for power system protection. This methodology helped in developing an intelligent fault diagnosis framework suitable for modern smart grid applications.

IV. RESULT

The result of the study shows that machine learning techniques can significantly improve the accuracy, speed, and reliability of fault detection and classification in electrical power systems. The simulated fault data were analyzed using different electrical parameters such as voltage, current, frequency variation, phase angle, and transient signal features. The machine learning model successfully identified normal and faulty conditions and classified major fault types such as single line-to-ground fault, line-to-line fault, double line-to-ground fault, and three-phase fault. Among the tested approaches, advanced classifiers such as Random Forest, Support Vector Machine, and Artificial Neural Network produced better performance than traditional threshold-based methods because they were able to learn complex fault patterns from the input data. The model showed high classification accuracy for balanced and unbalanced faults, especially when voltage and current features were combined with signal preprocessing methods. The result also indicates that fault detection time was reduced because the trained model could recognize abnormal patterns immediately after fault occurrence. This helps in quick isolation of the faulty section and reduces the possibility of equipment damage, power interruption, and system instability. The comparative result further shows that machine learning-based fault diagnosis is more suitable for modern smart power systems where operating conditions change frequently due to renewable energy integration, variable load demand, and bidirectional power flow. Traditional relay-based techniques may face difficulty under high fault resistance, noisy measurement, or dynamic grid conditions, while machine learning algorithms maintain better adaptability and classification performance. The study also found that the quality of training data, feature extraction, and proper model selection strongly affect the final output. When the dataset included different fault locations, fault resistance values, and loading conditions, the model became more robust and reliable. Overall, the result confirms that machine learning provides an efficient and intelligent solution for fault detection and classification in electrical power systems. It improves protection decision-making, reduces outage duration, supports predictive maintenance, and enhances the reliability of smart grid operation.

Bar Graph



The bar graph presents the fault detection accuracy of different machine learning algorithms used in electrical power systems. The graph compares five algorithms: Decision Tree, K-Nearest Neighbour, Support Vector Machine, Random Forest, and Artificial Neural Network. Among these, Artificial Neural Network achieved the highest accuracy with 97%, showing its strong ability to learn complex and nonlinear fault patterns from voltage and current signals. Random Forest also performed very well with 96% accuracy because it combines multiple decision trees and reduces classification errors. Support Vector Machine recorded 93%, indicating reliable performance in separating different fault classes. K-Nearest Neighbour achieved 90%, while Decision Tree showed the lowest accuracy at 88%. Although Decision Tree is simple and easy to understand, its performance is slightly weaker than advanced models. Overall, the graph shows that intelligent machine learning methods improve fault detection accuracy and support faster, more reliable protection decisions in modern power systems.

V. CONCLUSION

Machine learning-based fault detection and classification in electrical power systems provides an intelligent and reliable approach for improving power system protection. The study shows that machine learning algorithms can effectively analyze voltage, current, frequency, and transient signal features to identify abnormal operating conditions and classify different fault types. Compared with traditional relay-based and threshold-based protection methods, machine learning models offer higher accuracy, faster response, and better adaptability under changing load conditions, renewable energy integration, and complex grid disturbances. The comparative analysis indicates that advanced algorithms such as Artificial Neural Network and Random Forest perform better than simpler methods like Decision Tree and K-Nearest Neighbour. These models can learn nonlinear fault patterns and provide accurate classification of line-to-ground, line-to-line, double-line-to-ground, and three-phase faults. Faster fault identification helps in quick isolation of faulty sections, reducing equipment damage, outage duration, and system instability. Overall, the study concludes that machine learning is a powerful tool for modern smart grid protection and predictive maintenance. However, successful implementation depends on high-quality data, proper feature extraction, model validation, and real-time testing. Future work may focus on deep learning, real-time monitoring, and hybrid protection systems for more robust power system fault diagnosis.

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