

DETECTION, CLASSIFICATION, AND RATING OF ELECTRICAL FAULTS AND POWER QUALITY

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Abstract: Power system faults are unavoidable and can seriously damage costly equipment such as generators, transformers, and motors. They may also cause overvoltages, high fault currents, power outages, explosions, and even loss of life. Therefore, an effective protection system is required for fast fault detection, classification, and localization. Accurate fault analysis helps ensure reliable power supply, reduce outages, and protect electrical infrastructure. This study presents a framework for detecting, classifying, and locating power system faults. Its objectives are to identify different fault conditions at various locations and resistances, determine the causes of interruptions, support quick power restoration, and reduce recurring failures. The study also improves understanding of protection system components to minimize equipment damage and service disruptions. Advanced machine learning techniques, including Convolutional Neural Networks (CNN), K-Nearest Neighbors (KNN), Random Forest (RF), and Decision Tree (DT), are used for fault analysis. These models identify fault types, locate faults, classify disturbances, and assess power quality across five classes. Implemented in MATLAB/Simulink on a test network, the proposed framework effectively addresses fault detection, classification, localization, and power quality assessment, improving the protection, stability, and efficiency of modern power systems.

Keywords: Electric fault, phase, Fault location, Quality classification

Introduction

The rapid expansion of electrical power systems has significantly increased the number and length of transmission lines. These lines are vulnerable to faults caused by lightning, short circuits, equipment failures, overloading, aging, human errors, and improper operation [1]. Faults must be detected, classified, and located quickly to restore power and maintain system reliability. Fast and accurate fault localization is particularly important for transient faults, which may result from contaminated insulators, vegetation interference, or other temporary conditions [2–3].

A reliable protection system is essential to ensure uninterrupted power supply, minimize service interruptions, and prevent damage to electrical equipment. Such systems must rapidly identify, classify, and locate faults. Effective fault analysis helps determine the root causes of outages, supports quick restoration of power, and enables the implementation of preventive measures to reduce future occurrences.

Traditionally, fault diagnosis relied on manual inspection and conventional analytical techniques. However, these methods often suffer from limitations in accuracy, speed, and adaptability to varying fault conditions. Recent advances in machine learning have created new opportunities for improving fault analysis. By processing large volumes of data and identifying hidden patterns, machine learning algorithms can provide accurate fault

detection, classification, and localization.

This paper proposes an advanced fault analysis framework for electrical power systems. The objective is to accurately identify and classify different fault types occurring at various locations and fault resistances, determine the causes of system disturbances, facilitate rapid power restoration, and reduce fault recurrence. The study also aims to improve understanding of protection system components, enabling the implementation of effective preventive measures and reducing equipment damage and service disruptions.

To achieve these objectives, machine learning techniques such as Convolutional Neural Networks (CNN), K-Nearest Neighbors (KNN), Random Forest (RF), Decision Tree (DT), and Support Vector Machine (SVM) are employed. These algorithms are used to improve fault detection, classification, and location estimation. In addition, the proposed framework categorizes power quality conditions into different classes, providing a comprehensive assessment of system performance.

The performance of these machine learning models is evaluated and compared to determine the most effective approach for power system fault analysis. The findings provide valuable insights into the strengths and limitations of each algorithm and contribute to the development of more reliable fault diagnosis techniques. Overall, this research addresses the challenges of fault detection, classification, and localization in power systems and presents a comprehensive solution for enhancing system reliability, reducing outages, minimizing equipment damage, and improving the resilience of modern electrical networks.

Power system faults can generally be classified into three categories: symmetrical faults, unsymmetrical faults, and other faults. Symmetrical faults involve all three phases equally and produce the highest fault currents. Unsymmetrical faults, including line-to-

ground (LG), line-to-line (LL), and double line-to-ground (LLG) faults, are more common and create unbalanced system conditions. Other faults include open conductor faults, insulation failures, overloads, and equipment malfunctions. Accurate detection and classification of these faults are critical for maintaining system stability and ensuring reliable power delivery.

A. Symmetrical Faults

Symmetrical (balanced) faults are severe but occur infrequently, accounting for only 2–5% of all power system faults [1]. They include **three-phase (L-L-L)** and **three-phase-to-ground (L-L-LG)** faults. Although the system remains balanced during these faults, they generate very high fault currents and can cause significant damage to power system equipment. Symmetrical faults are relatively easy to analyze on a per-phase basis and are important for determining relay settings, circuit breaker rupturing capacity, and protective switchgear ratings.

. Non-Symmetrical Faults

Non-symmetrical (unbalanced) faults are more common and less severe than symmetrical faults. They include line-to-ground (LG), line-to-line (LL), and double line-to-ground (LLG) faults [1]. Among these, LG faults are the most frequent, accounting for 65–70% of all faults, followed by LLG faults (15–20%) and LL faults (5–10%). These faults occur when conductors come into contact with the ground or with each other. Since they create unequal phase impedances and currents, they cause system imbalance and are more complex to analyze than symmetrical faults. Electric power generation, transmission, and distribution systems are essential for modern society and require high reliability and continuity of service. A lack of situational awareness can lead to abnormal operation or widespread blackouts, making power system protection a critical area of research.

Fault detection and classification play a vital role in minimizing transmission line damage

and reducing outage duration. Various protection methods have been proposed in the literature. Research in [1] classifies faults using zero- and negative-sequence current and voltage components. In [2], Multi-Resolution Analysis (MRA) is employed to extract current signal features for fault classification. The study in [3] combines sequence component analysis with fault location techniques to identify both fault type and location.

Traditional expert knowledge-based approaches are limited by the availability of real fault data. To overcome this limitation, Machine Learning (ML) techniques automatically learn patterns from data and have become increasingly important in power system applications [4]. ML provides an effective solution for analyzing large-scale power system data and has been successfully applied to fault analysis [5]. Among ML techniques, supervised learning has been widely used for fault classification. However, it requires fully labeled datasets, which are often unavailable in real power systems. This limitation can result in fault misclassification. Semi-supervised learning addresses this issue by effectively utilizing both labeled and unlabeled data.

Previous work [7] applied semi-supervised K-Nearest Neighbor (KNN) algorithms for fault diagnosis and classification in small transmission systems, using fault current magnitude as the classification feature. Results showed good performance for systems with limited features. Building on this work, the present study proposes a method that combines suitable classifiers with a small amount of labeled data to classify unlabeled fault data. Discrete Wavelet Transform (DWT) is used to extract features from three-phase current and voltage waveforms, revealing important frequency-domain information. The extracted features are then used for fault classification. To identify the most effective classifier for transmission line

fault detection and classification, Convolutional Neural Network (CNN), K-Nearest Neighbor (KNN), and Decision Tree (DT) models are evaluated and compared. A key requirement of power systems is high reliability and uninterrupted service. Consequently, significant research has focused on improving system dependability through accurate fault detection, classification, and localization. A power system fault refers to any significant deviation in voltage, current, or frequency that disrupts normal operation and may adversely affect connected equipment.

Literature review

The increasing integration of distributed generation (DG), microgrids, modern generation loads, and advanced equipment into conventional power systems has created significant challenges for traditional protection schemes. Most of these technologies use power electronic interfaces and support bidirectional power flow, resulting in protection issues such as blinding of protection, false tripping, islanding, loss of coordination, and auto-recloser problems (Bansal, 2019; Sanchez et al., 2020; Telukunta et al., 2017) [1]. Consequently, power system operation and control have become more complex, making manual inspection and maintenance increasingly difficult. The likelihood of faults in modern power systems is also high due to protective device malfunctions, insulation degradation (Santis et al., 2017) [2], natural disasters such as floods, storms, lightning strikes, and heavy rainfall causing cable failures, as well as sudden load variations, switching operations, and elevated temperatures that lead to equipment overheating (Wang et al., 2016) [3]. These factors increase the vulnerability of complex power networks and highlight the need for more advanced protection mechanisms.

Objectives

- To provide a mechanism for precisely locating, classifying, and detecting faults in electrical power networks.
- To compare and assess the effectiveness of several machine learning techniques, such as Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors (KNN), Random Forest (RF), and Convolutional Neural Networks (CNN), in defect analysis.
- To better understand the protection system's components and the reasons of disruptions.
- To put precautions in place and lessen the possibility of service interruptions and equipment damage.
- To categorize power quality into separate groups in order to fully comprehend system behavior

methodology

Power system fault analysis is essential for ensuring a reliable power supply while minimizing interruptions and equipment damage. This study presents a comprehensive framework for the detection, classification, and localization of power system faults. The primary objectives are to accurately identify and classify faults occurring at different locations and fault resistances, determine the causes of system interruptions, facilitate rapid power restoration, and reduce the likelihood of recurring faults. The study also aims to improve understanding of protection system components, enabling the implementation of preventive measures that reduce service disruptions and equipment damage. The proposed framework employs machine learning techniques, including K-Nearest Neighbors (KNN), Random Forest (RF), and Decision Tree (DT), for accurate fault detection, classification, and fault location estimation. Additionally, the methodology classifies power quality conditions into five

distinct categories, providing a broader assessment of system performance. Overall, the proposed approach effectively addresses the challenges of fault detection, fault classification, fault localization, and power quality assessment in modern power systems

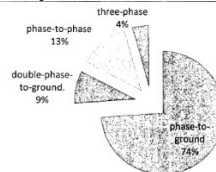


Figure 1 Percentage of fault across the systems

Analysis of power system faults is essential for assuring a steady supply of electricity. The goal of this study is to provide a thorough system for identifying, categorizing, and pinpointing the position of distinct fault types that can occur at various fault sites and with variable fault resistances. The study attempts to reduce further occurrences, identify the root causes of outages, and swiftly restore power. Additionally, knowing the parts of the protective system makes it possible to take preventative action to lessen service interruptions and equipment damage.

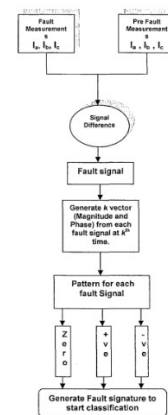


Figure . 2 Functional diagram for generating faults' signatures using the symmetrical patterns

Data Collection:

The system architecture for power system fault detection and classification begins with dataset collection, which includes key

parameters such as G, C, B, A, Ia, Ib, Ic, Va, Vb, Vc, and fault types. These variables provide important information about system operating conditions and fault occurrences. After collection, the dataset undergoes preprocessing, including data cleaning, handling missing values, and normalization. These steps improve data quality by reducing noise and inconsistencies, making the dataset suitable for analysis.

The preprocessed dataset is then divided into training and testing sets. The training set is used to train machine learning models, enabling them to learn patterns and relationships within the data, while the testing set is used to evaluate model performance and accuracy. The proposed framework employs several machine learning algorithms, including Convolutional Neural Networks (CNN), Random Forest (RF), K-Nearest Neighbors (KNN), Decision Tree (DT), and Support Vector Machine (SVM), for fault detection and classification. During training, labeled data are provided to the algorithms, allowing them to optimize their parameters and accurately identify different fault types. Cross-validation techniques may also be applied to improve model robustness and generalization.

After training, the models are evaluated using the testing dataset. Their performance is compared based on classification accuracy and prediction capability to identify the most effective model. The selected model is then used for accurate fault detection and classification across different fault locations and fault resistances, providing valuable insights into the causes of system disturbances and supporting rapid power restoration. In addition to fault classification, the framework incorporates fault localization, where the trained model, along with system measurements and network topology information, is used to determine the fault location. This information assists maintenance personnel in performing targeted repair and

restoration activities. Overall, the proposed architecture integrates data collection, preprocessing, model training, evaluation, fault classification, and fault localization to ensure accurate fault analysis, improve system reliability, minimize outages, and reduce equipment damage.

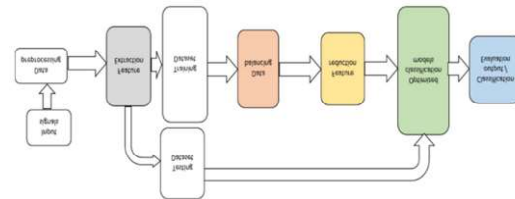


Figure 3 Machine learning approach for fault detection and classification.

Fault Types and Classification:

The methodology considers various fault types, including phase-to-ground (LG) faults, phase-to-phase (LL) faults, double phase-to-ground (LLG) faults, three-phase (LLL) faults, and three-phase-to-ground (LLLG) symmetrical faults. To accurately detect and classify these faults, the proposed framework employs machine learning algorithms, including Convolutional Neural Networks (CNN), K-Nearest Neighbors (KNN), Random Forest (RF), and Decision Tree (DT). These algorithms were selected for their strong performance in handling multi-class classification problems and their ability to accurately identify different fault conditions...

Power Quality Classification:

Power Quality Classification: Power quality conditions are categorized into five predefined classes based on industry standards and parameters such as voltage variations, harmonics, and transients. For this task, Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbors (KNN) algorithms are employed due to their effectiveness in multi-class classification. The preprocessed dataset is divided into training and testing sets, and the selected models are trained and optimized through parameter tuning to improve classification performance. Model effectiveness is evaluated using metrics such

as accuracy, precision, recall, F1-score, and confusion matrix, enabling comparison of their ability to correctly classify power quality conditions. The proposed framework provides a comprehensive solution for fault detection, fault classification, fault localization, and power quality classification in power systems. By leveraging machine learning techniques such as CNN, KNN, Random Forest, and Decision Tree, the framework achieves accurate analysis of system disturbances, supports rapid power restoration, and facilitates the implementation of preventive measures to reduce recurring faults and equipment damage. This approach serves as a valuable reference for researchers and practitioners in the fields of power systems and machine learning..

Simulation and results

This section presents the results of the proposed machine learning and deep learning framework for power system fault detection, fault classification, and power quality assessment. The analysis was performed using current and voltage measurements obtained from a three-phase transmission system under both normal and fault conditions. The primary objective was to evaluate the capability of artificial intelligence techniques in detecting faults, classifying fault types, and assessing power quality disturbances. Three datasets were used in this study. The first dataset was utilized for binary fault detection, the second dataset for multiclass fault classification, and the third dataset for power quality disturbance classification.

Table 1 Dataset Summary

Dataset	Purpose	Samples	Features
DDTR	Fault Detection	12,001	7
CLTS	Fault Classification	7,861	10
Power	Power	11,998	129

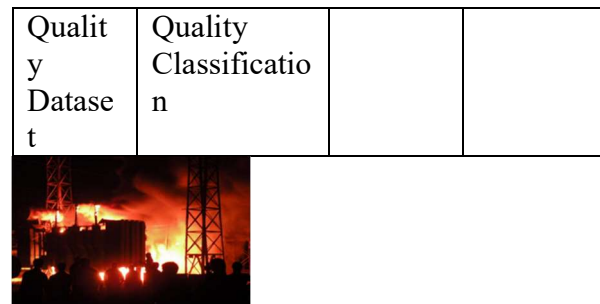


Figure 4 Fire due to Faults

Electrical faults can lead to equipment damage, power outages, overheating, and fire hazards. Therefore, an accurate fault detection and classification framework is essential for ensuring system reliability, operational safety, and continuous power supply..

Binary Fault Detection Using Neural Network

The first stage of the proposed framework focused on binary classification, where the objective was to determine whether the system was operating under normal or fault conditions. Six electrical parameters, namely phase currents (Ia, Ib, and Ic) and phase voltages (Va, Vb, and Vc), were used as input features. The dataset was split into 80% training and 20% testing data, resulting in 9,600 training samples and 2,401 testing samples. A feedforward Neural Network was developed and trained for five epochs. During training, the model learned the relationship between the electrical measurements and the operating condition of the system, enabling effective fault detection..

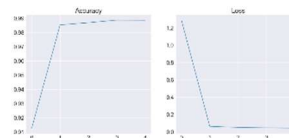


Figure 5.CNN Accuracy and Loss Curves

As illustrated in Figure , the model exhibited rapid convergence during training. The training accuracy increased steadily, while the loss value decreased significantly with each epoch. The close agreement between training and validation performance demonstrates that the model generalized effectively without significant overfitting. The trained model was

subsequently evaluated using previously unseen test samples.

Table 2 Binary Fault Detection Performance

Metric	Value (%)
Accuracy	99.04
Precision	99.82
Recall	98.10
F1-Score	99.00

The results presented in Table demonstrate the excellent performance of the Neural Network model. The model achieved an accuracy of 99.04%, indicating that it correctly classified almost all testing samples. The high precision shows that only a few normal conditions were misclassified as faults, while the strong recall value highlights the model's effectiveness in accurately detecting actual fault events.



Figure 6 Binary Classification Confusion Matrix

The confusion matrix shown in Figure further validates the effectiveness of the proposed model. Out of 2,401 testing samples, only a small number were misclassified. Specifically, 1,295 normal operating conditions and 1,083 fault conditions were correctly identified. This confirms the robustness of the proposed Neural Network for practical fault detection applications. Overall, the binary classification results indicate that the developed Neural Network can reliably distinguish between healthy and faulty operating conditions with very high accuracy.

Exploratory Data Analysis for Multiclass Classification

Before developing the multiclass fault classification models, an exploratory data analysis (EDA) was conducted to examine the dataset characteristics. The dataset contained 7,861 observations and 10 variables, including

electrical measurements and fault indicators. A correlation analysis was performed to identify relationships among the variables and gain insights into the underlying data patterns

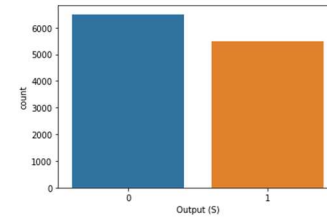


Figure 7 Count vs output

The correlation plot shown in Figure illustrates the relationships among the current, voltage, and fault variables. Several strong correlations were identified, indicating that the selected features contain valuable information for effective fault classification. To gain further insight into system behavior, distribution analysis was performed on all three-phase current and voltage measurements, allowing the variation and patterns of the electrical parameters to be examined under different operating conditions.

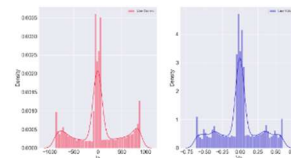


Figure 8 Current and Voltage Distribution Line A

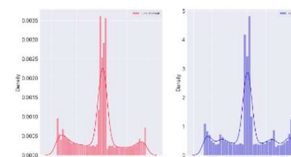


Figure 9 Current and Voltage Distribution Line B

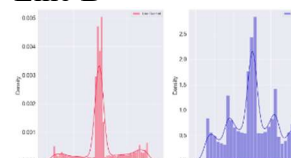


Figure 10 Current and Voltage Distribution Line C

he distribution plots showed variations in current and voltage signals under different

operating conditions. Current measurements exhibited greater variability than voltage measurements, indicating higher sensitivity to faults. A statistical summary of the electrical measurements is provided in Table 3.

Table 3 Statistical Summary of Electrical Parameters

Parameter	Minimum	Maximum	Mean
Ia	-883.54	885.74	13.72
Ib	-900.53	889.87	-44.85
Ic	-883.36	901.27	34.39
Va	-0.62	0.60	-0.01
Vb	-0.61	0.63	0.00
Vc	-0.61	0.60	0.01

The statistics indicate substantial variations in current magnitudes, particularly during fault conditions. Voltage values remained within a relatively smaller range and were represented in per-unit form. No missing values or duplicate observations were identified during data inspection. Therefore, no additional data cleaning or imputation procedures were required.

Fault Type Generation and Multiclass Classification

The multiclass fault classification problem was formulated by combining the four fault indicators (G, C, B, and A) into a single fault label.

Table 4 Fault Type Representation

Fault Code	Fault Type
0000	No Fault
1001	LG Fault
0011	LL Fault
1011	LLG Fault
0111	LLL Fault
1111	LLLG Fault

This transformation converted the multiple binary outputs into a single multiclass target variable, allowing the classification models to identify the exact fault category.

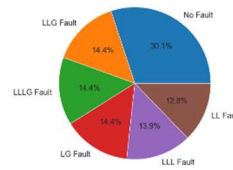


Figure 11 Fault Category Distribution

The pie chart shown in Figure indicates that all fault categories are represented within the dataset. The relatively balanced class distribution minimizes classification bias and improves model generalization. Further analysis was conducted to examine the behavior of current and voltage measurements under normal and fault conditions.

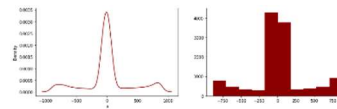


Figure 12 Current Distribution for Phase A

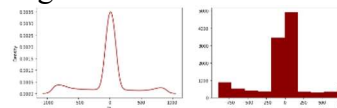


Figure 13 Current Distribution for Phase B

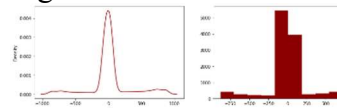


Figure 14 Current Distribution for Phase C

The current distributions demonstrate significant variations caused by different fault conditions. Fault events produce abrupt increases in current magnitude, creating distinguishable patterns that can be effectively learned by machine learning models.

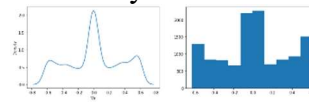


Figure 15 Voltage Distribution for Phase A

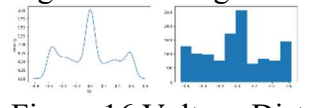


Figure 16 Voltage Distribution for Phase B

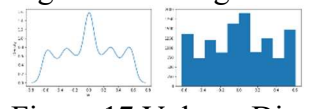


Figure 17 Voltage Distribution for Phase C

The voltage distributions exhibit disturbances during fault conditions while remaining relatively stable during normal operation. To

further evaluate data variability, boxplot analysis was performed.



Figure 18 Boxplot Analysis for Line A

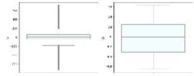


Figure 19 Boxplot Analysis for Line B

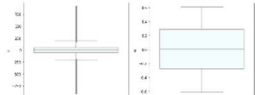


Figure 20 Boxplot Analysis for Line C

The boxplots reveal a relatively normal distribution with several extreme observations corresponding to fault conditions. These extreme values represent genuine system behavior rather than measurement errors. The current-voltage relationship analysis showed that normal operating currents typically remain within ± 100 A. During fault events, current magnitudes increased significantly and frequently exceeded ± 800 A. Simultaneously, noticeable voltage disturbances were observed, confirming the effectiveness of current and voltage measurements as fault indicators.

Machine Learning-Based Fault Classification

To identify the most suitable classifier for fault diagnosis, four machine learning algorithms were evaluated:

- Support Vector Machine (SVM)
- Decision Tree (DT)
- K-Nearest Neighbors (KNN)
- Random Forest (RF)

The models were evaluated using 10-fold cross-validation.

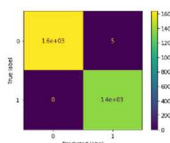


Figure 21 SVM Confusion Matrix

The SVM model achieved an average

classification accuracy of 99.70%. The confusion matrix reveals very few classification errors, demonstrating the model's ability to effectively distinguish among different fault categories.

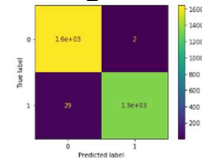


Figure 22 Decision Tree Confusion Matrix

The Decision Tree model achieved an accuracy of 99.40%. The classifier successfully identified most fault categories while maintaining the advantage of interpretability.



Figure 23 Decision Tree Visualization

Figure provides a graphical representation of the decision-making process learned by the classifier. The tree highlights the importance of current and voltage parameters in fault identification.

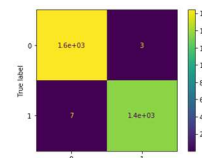


Figure 24 KNN Confusion Matrix

The KNN model achieved an accuracy of 99.57%, demonstrating highly competitive performance and minimal misclassification rates.

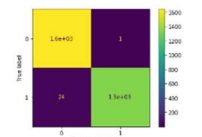


Figure 25 Random Forest Confusion Matrix

The Random Forest model achieved an accuracy of 99.10%. Although slightly lower than the other models, it still demonstrated excellent classification capability. The overall performance comparison is presented in Table 5.

Table 5 Comparison of Fault Classification

Models

Model	Accuracy (%)
SVM	99.70
KNN	99.57
Decision Tree	99.40
Random Forest	99.10

Among all evaluated classifiers, SVM achieved the highest accuracy and produced the fewest classification errors. The results indicate that SVM is the most effective model for multiclass power system fault classification within the investigated dataset.

Power Quality Dataset Preparation

For power quality analysis, a separate dataset containing 11,998 samples and 129 attributes was used. The output variable was separated from the input features, and Fast Fourier Transform (FFT) was applied to extract frequency-domain characteristics associated with power quality disturbances. The features were then normalized and divided into 9,598 training samples and 2,400 testing samples. The results demonstrate the effectiveness of machine learning and deep learning techniques for intelligent power system monitoring. The Neural Network achieved a fault detection accuracy above 99%, successfully distinguishing between normal and faulty conditions. Exploratory analysis showed that faults introduce significant disturbances in current and voltage signals, creating patterns that can be learned by AI models. Among the multiclass classifiers, SVM achieved the highest accuracy of 99.70%, followed by KNN, Decision Tree, and Random Forest. Its superior performance is attributed to its ability to construct optimal decision boundaries in high-dimensional feature spaces. The results confirm that current and voltage measurements provide sufficient information for accurate fault diagnosis. Moreover, the combination of FFT-based feature extraction and machine learning proved effective for power quality assessment. Overall, the proposed framework

demonstrated high accuracy, reliability, and generalization capability, making it suitable for modern smart grid and power system protection applications.

Conclusion

. This thesis applied machine learning techniques for power system fault detection, fault classification, and power quality classification. The considered faults included phase-to-ground (LG), phase-to-phase (LL), double phase-to-ground (LLG), three-phase (LLL), and three-phase-to-ground (LLLG) faults. In addition, power quality was categorized into five classes. The performance of Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) was evaluated for fault analysis. The results showed that SVM achieved the best fault detection performance, providing high accuracy and reliable identification of fault conditions. Its ability to accurately predict different fault types makes it a valuable tool for improving power system reliability, minimizing downtime, and supporting timely maintenance actions. The study also demonstrated the importance of power quality classification, which provides insights into system health and helps identify disturbances requiring corrective measures. Although the findings highlight the effectiveness of SVM, algorithm performance may vary across different power system configurations and datasets. Therefore, further validation on diverse systems is recommended. Overall, this paper contributes to the field of power system fault analysis by comparing multiple machine learning techniques and demonstrating the effectiveness of SVM for fault detection. Future work may focus on integrating SVM with other algorithms and implementing real-time fault detection systems to further enhance power system reliability and performance.

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