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Multiclass Electrical Fault Classification in Three-Phase Power Systems Using Random Forest, Support Vector Machine, and XGBoost

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Abstract: Electrical fault classification in three-phase power systems remains challenging because different fault conditions can exhibit similar current and voltage characteristics, limiting the diagnostic capability of conventional binary fault detection. This study aimed to compare the performance of Random Forest, Support Vector Machine, and Extreme Gradient Boosting (XGBoost) for multiclass electrical fault classification and to identify the most effective and stable model. The publicly available Electrical Fault Detection and Classification dataset obtained from the Kaggle repository was used in this study. The dataset contains 7,861 observations with six electrical features comprising three-phase currents (Ia, Ib, and Ic) and voltages (Va, Vb, and Vc), which were used to classify six operating conditions: Normal, Line-to-Ground, Line-to-Line, Double Line-to-Ground, Three-Phase, and Three-Phase-to-Ground faults. The models were evaluated using accuracy, precision, recall, F1-score, and five-fold stratified cross-validation, complemented by confusion-matrix and feature-importance analyses. Random Forest achieved the best test performance with an accuracy of 86.78% and an F1-score of 86.76%, while cross-validation produced a mean accuracy of 87.55% and a mean F1-score of 87.53%. Class-level analysis revealed that Three-Phase and Three-Phase-to-Ground faults were the most difficult conditions to distinguish because of substantial overlap in their electrical characteristics. The findings demonstrated that Random Forest provided the most effective and stable classification performance and that combining performance, stability, and class-level analyses provided deeper insight into multiclass electrical fault diagnosis.

Keywords: Electrical Fault Classification; Three-Phase Power System; Machine Learning; Random Forest; Multiclass Classification.

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1. Introduction

The reliability of electrical power systems is essential for supporting societal activities and industrial operations, as these systems constitute a fundamental component of modern infrastructure. Three-phase power systems are widely employed in electricity transmission and distribution because of their efficiency and capability to accommodate substantial electrical loads (Pillai *et al.*, 2024). Maintaining the reliability and continuity of power supply is therefore critical, since electrical disturbances may result in power quality degradation, equipment damage, operational disruption, and, in severe cases, complete power outages (Almagrahi, 2025). As power systems become increasingly complex, effective protection mechanisms are required to maintain system integrity and minimize the consequences of abnormal operating conditions. In this context, rapid and accurate detection and identification of electrical faults are essential to prevent fault propagation and support reliable system operation (Nolasco *et al.*, 2005). Consequently, the development of reliable fault detection and classification approaches has become increasingly important for improving the reliability, safety, and continuity of three-phase power systems (Alvarez-Alvarado *et al.*, 2024). In three-phase power systems, fault classification is a critical task because electrical disturbances may occur in different configurations, including Line-to-Ground (LG), Line-to-Line (LL), Double Line-to-Ground (LLG), Three-Phase (LLL), and Three-Phase-to-Ground (LLLG) faults. These fault conditions produce changes in three-phase current and voltage characteristics that can be utilized to distinguish abnormal operating conditions. Conventional rule-based approaches have classified faults by examining voltage sag and current swell characteristics under different fault resistances and locations; however, their effectiveness may decrease as network conditions and fault characteristics become more complex (Awalin *et al.*, 2025). Signal-processing approaches, particularly the Discrete Wavelet Transform (DWT), have also been combined with decision rules or Artificial Neural Networks (ANNs) to extract transient characteristics and improve fault discrimination (Malla *et al.*, 2019). More recent learning-based approaches, including Extreme Learning Machines and adaptive neural networks, have further demonstrated the potential of data-driven methods for handling variations in fault type, resistance, and inception conditions (Assadi & Salhi, 2023). Nevertheless, multiclass fault classification remains challenging when different fault categories exhibit similar electrical characteristics, requiring classification methods capable of learning complex multivariate and nonlinear relationships among current and voltage measurements. Machine learning (ML) provides a data-driven approach to electrical fault classification, overcoming some limitations of conventional rule-based methods in handling complex and nonlinear fault patterns (Basnet & Sen, 2025). Among various ML algorithms, Random Forest (RF), Support Vector Machine (SVM), and XGBoost have demonstrated strong potential for classifying power system faults due to their distinct learning mechanisms (Mandal & Bohre, 2022; Oishi *et al.*, 2023; Zhou *et al.*, 2024). However, their performance may vary across fault types, datasets, and operating conditions, indicating that no single algorithm can be assumed to be universally superior. Therefore, a comparative evaluation of RF, SVM, and XGBoost is necessary to determine their effectiveness for multiclass fault classification in three-phase power systems. Previous research by Yasin *et al.* (2026) developed a leakage-aware framework for fault detection in three-phase power systems using an Artificial Neural Network (ANN) and scenario-based data splitting. The study formulated fault detection as a binary classification problem between normal and fault conditions and compared ANN with Logistic Regression, Support Vector Machine (SVM), and Random Forest.

The results demonstrated high fault-detection performance, with an AUC of 0.987 and an accuracy of approximately 98.5%, while Random Forest achieved the best comparative performance. These findings demonstrate the effectiveness of machine learning for three-phase fault detection and provide a foundation for extending the analysis toward the identification of specific fault categories. Furthermore, recent studies have demonstrated varying performances of machine learning algorithms in electrical fault and power quality classification. Random Forest has achieved high classification performance in power distribution and power quality applications (Abro *et al.*, 2025; Soundharya *et al.*, 2025), while SVM has also shown strong fault classification capability, particularly with appropriate kernel configurations (Goyal *et al.*, 2024). XGBoost has similarly demonstrated high performance in power quality disturbance classification when combined with suitable feature extraction techniques (Yu *et al.*, 2024). However, model performance may vary depending on dataset characteristics, fault types, noise levels, and feature representations (Palomares-Salas *et al.*, 2025). Therefore, comparative assessment should consider not only overall accuracy but also precision, recall, and F1-score to provide a more comprehensive evaluation of model performance across fault classes. Despite these advances, an important research gap remains in moving from binary fault detection toward specific multiclass fault identification. Previous work by Yasin *et al.* (2026) successfully distinguished normal and fault conditions but did not differentiate specific fault types, thereby limiting the diagnostic information provided. Multiclass fault classification is inherently more challenging because different fault categories may exhibit overlapping electrical signal characteristics (Alaca *et al.*, 2024; Anwar *et al.*, 2025). Furthermore, relying solely on overall accuracy may obscure class-specific classification errors and model instability. Therefore, further investigation is required to evaluate multiclass fault classification using comprehensive performance metrics,

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cross-validation, and class-level misclassification analysis. To address this gap, this study extends binary fault detection toward multiclass fault classification using 7,861 observations characterized by six three-phase electrical features (Ia, Ib, Ic, Va, Vb, and Vc) and six classes (Normal, LG, LL, LLG, LLL, and LLLG). Random Forest, SVM, and XGBoost are comparatively evaluated using accuracy, precision, recall, and F1-score, complemented by five-fold stratified cross-validation to assess model stability. Beyond overall predictive performance, confusion matrices and feature importance are employed to examine class-level misclassification patterns and the relative contribution of electrical features. The novelty of this study lies in integrating multiclass fault identification with model stability, feature interpretation, and class-level error analysis, thereby providing a more comprehensive assessment than conventional binary fault detection (Ghaly, 2025; Uzel *et al.*, 2025; Xin *et al.*, 2025). Accordingly, this study aims to compare the performance of Random Forest, Support Vector Machine (SVM), and XGBoost in classifying six operating and fault conditions in three-phase power systems and to identify the most effective classification model. The study further evaluates model stability through cross-validation, identifies fault classes that are most susceptible to misclassification, and examines the relative contribution of current and voltage features to model decisions. Through this approach, the study is expected to provide empirical evidence for machine learning-based fault diagnosis while offering deeper insights into feature contributions and the primary sources of classification errors in three-phase power systems.

2. Related Work

Fault detection and classification in three-phase power systems have evolved from conventional signal-processing techniques toward data-driven machine learning (ML) approaches. Traditional methods, including Discrete Wavelet Transform and phase-angle-based techniques, remain useful for extracting fault characteristics but may face limitations when dealing with complex, noisy, and nonlinear electrical signals (Daang *et al.*, 2024; Mukherjee *et al.*, 2025). Consequently, ML methods have gained increasing attention because of their ability to learn fault patterns directly from current and voltage measurements and adapt to diverse operating conditions (Nandhini & Prajith, 2023; Sarmiento *et al.*, 2024). Recent studies have employed Random Forest (RF), Support Vector Machine (SVM), XGBoost, Artificial Neural Networks (ANN), and deep learning architectures such as CNN and LSTM for both binary and multiclass fault classification (Basnet & Sen, 2025). These developments indicate a continuing shift toward intelligent, data-driven fault diagnosis to improve the reliability and efficiency of power systems.

2.1 State-of-the-art Research

Fault detection and classification (FDC) methods in power systems have evolved from conventional signal-processing techniques toward machine learning (ML) and deep learning (DL) approaches. Traditional methods such as the Discrete Wavelet Transform (DWT) have been widely employed to extract transient fault characteristics, but they often depend on manual feature extraction and may face limitations in handling complex nonlinear and nonstationary signals (Daang *et al.*, 2024; Mukherjee *et al.*, 2025). The emergence of ML introduced data-driven algorithms such as K-Nearest Neighbor (KNN), Decision Tree (DT), and Support Vector Machine (SVM), enabling more adaptive fault detection and classification (Ponukumati *et al.*, 2022). More recently, DL architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, have expanded automatic feature-learning capabilities for complex fault patterns (Sridevi *et al.*, 2023). Nevertheless, conventional ML models remain relevant because they can provide competitive classification performance with lower computational complexity, particularly for structured electrical datasets (Briza *et al.*, 2024). The development of fault diagnosis in power systems has progressively shifted from binary fault detection toward multiclass fault classification. While binary approaches primarily distinguish normal and faulty operating conditions, multiclass classification provides more detailed diagnostic information by identifying specific fault categories such as Line-to-Ground (LG), Line-to-Line (LL), Double Line-to-Ground (LLG), Three-Phase (LLL), and Three-Phase-to-Ground (LLLG) faults. This transition is important because identifying the specific fault type can provide more informative diagnostic support than merely detecting the presence of a fault. However, multiclass classification introduces greater complexity because different fault categories may exhibit overlapping current and voltage characteristics under varying operating conditions (Awalin *et al.*, 2025). Consequently, recent research has increasingly focused on data-driven classification methods capable of distinguishing multiple fault categories from complex electrical signal patterns. Recent studies have demonstrated the effectiveness of Random Forest (RF), Support Vector Machine (SVM), and XGBoost for electrical fault classification. SVM has shown strong capability in distinguishing complex fault patterns, achieving competitive performance in power-grid fault classification. Meanwhile, tree-based ensemble methods such as RF and XGBoost have demonstrated high classification performance due to their ability to capture nonlinear relationships among electrical features and maintain robustness under

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complex operating conditions (MeenaPrakash *et al.*, 2025; Oishi *et al.*, 2023). In transmission-line fault classification, RF and XGBoost have also achieved highly competitive results, highlighting the potential of ensemble learning for multiclass fault diagnosis. Nevertheless, differences in datasets, fault configurations, feature representations, and evaluation procedures make direct performance comparisons difficult. Therefore, a consistent comparative evaluation of RF, SVM, and XGBoost on the same multiclass fault dataset is necessary to assess their relative effectiveness. Previous research by Yasin *et al.* (2026) developed a leakage-aware fault detection framework for three-phase power systems using an Artificial Neural Network (ANN) and scenario-based data splitting. The study formulated fault detection as a binary classification problem between normal and fault conditions and compared ANN with Logistic Regression, Support Vector Machine (SVM), and Random Forest. The proposed framework achieved an AUC of 0.987 and an accuracy of approximately 98.5%, while Random Forest demonstrated the best comparative performance. Despite these promising results, the study was limited to binary classification and did not distinguish specific fault types, leaving an opportunity for further development toward multiclass fault diagnosis. Collectively, previous studies demonstrate that machine learning provides considerable potential for electrical fault detection and classification; however, model performance remains dependent on fault characteristics, feature representation, and evaluation strategies. A particularly important research direction is the transition from binary fault detection toward multiclass diagnosis capable of identifying specific fault categories. Building on previous work, the present study compares Random Forest, SVM, and XGBoost for classifying six operating conditions (Normal, LG, LL, LLG, LLL, and LLLG) using three-phase current and voltage measurements. The evaluation combines accuracy, precision, recall, and F1-score with five-fold stratified cross-validation, confusion-matrix analysis, and feature importance. This framework positions the present study beyond overall predictive accuracy by additionally examining model stability, feature contributions, and class-level misclassification patterns.

2.2 Comparison with Previous Studies

Previous studies on electrical fault detection and classification have employed various machine learning (ML) and deep learning (DL) approaches with different classification objectives, datasets, features, and evaluation strategies. Algorithms such as Random Forest (RF), Support Vector Machine (SVM), XGBoost, and Artificial Neural Networks (ANN) have demonstrated promising performance, although their effectiveness varies across fault scenarios and dataset characteristics (Oishi *et al.*, 2023). Previous research has also employed both simulated and real-world datasets, which differ in dimensionality, noise characteristics, fault configurations, and data complexity. Consequently, high classification accuracy reported in one study cannot be directly interpreted as superior performance over another without considering differences in datasets, classification scope, and experimental design (Liu & Liu, 2024; Tshodi *et al.*, 2024). Therefore, previous studies should be compared comprehensively based on their methods, datasets, evaluation metrics, performance, strengths, and limitations rather than predictive accuracy alone. Previous studies have employed diverse machine learning models and datasets for power system fault detection and classification. Otudi *et al.* (2022) compared SVM, RF, and XGBoost using PMU measurements supplemented with simulated data and reported a classification accuracy of 98.58%. Xin *et al.* (2025) employed a two-stage CatBoost–LightGBM framework using simulated circuit data, while Rafi *et al.* (2024) combined ANN and SVM using current and voltage features generated through MATLAB SimPowerSystem. Hybrid approaches have also been investigated, including an Optuna-optimized ANN–RF model with SMOTE that achieved 99.8% accuracy on synthetic MATLAB/Simulink data (Uzel *et al.*, 2025). In a closely related study, Yasin *et al.* (2026) developed an ANN-based leakage-aware framework using current, voltage, and energy-related features with scenario-based data splitting to distinguish normal and fault conditions. Meanwhile, Hou *et al.* (2025) employed RF with multi-feature fusion on an experimental platform and reported over 99% accuracy for high-impedance fault detection. Overall, these studies demonstrate strong predictive performance across different approaches; however, variations in data sources, feature representations, fault scenarios, and classification objectives limit direct comparisons of their reported performance. Previous studies have adopted different evaluation strategies to assess electrical fault detection and classification models. While some studies primarily report overall accuracy, others employ multiple metrics, including precision, recall, F1-score, and Area Under the Curve (AUC), to provide a more comprehensive assessment of predictive performance. For example, Yasin *et al.* (2026) evaluated binary fault detection using multiple metrics and reported an AUC of 0.987 with an accuracy of approximately 98.5%, supported by cross-validation and scenario-based evaluation. Other studies have also reported high classification performance, although differences in fault categories, datasets, feature representations, and validation procedures make direct numerical comparisons difficult. Therefore, model performance should be interpreted within the context of classification complexity and evaluation design, particularly when comparing binary fault detection with multiclass fault classification. Each machine learning approach offers distinct strengths and limitations for electrical fault analysis. ANN is effective in capturing nonlinear relationships among electrical variables, although previous work has primarily applied it to binary normal–fault detection without distinguishing specific fault categories (Yasin *et al.*, 2026). Random Forest provides robust

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performance on structured data and supports feature-importance analysis, although its effectiveness depends on the separability of fault characteristics. SVM can construct effective decision boundaries for complex classification problems but is sensitive to feature scaling and parameter selection, whereas XGBoost provides strong predictive capability through gradient boosting but requires appropriate hyperparameter configuration. Feature-engineering and hybrid approaches may further improve fault representation, although they can increase computational and methodological complexity. These strengths and limitations indicate an opportunity for evaluating RF, SVM, and XGBoost within a consistent multiclass framework to determine not only their predictive performance but also their stability and class-specific classification behavior.

Table 1. Comparison of Previous Studies on Electrical Fault Detection and Classification

Study	Data / Classification	Method	Evaluation	Main Findings	Limitation
Malhotra *et al.* (2018)	Electrical fault signals; multiclass faults	DWT and rule-based decision approach	Classification performance	Wavelet-based signal decomposition supported discrimination among different fault conditions	Relies on signal transformation and predefined fault indices
Goyal *et al.* (2024)	Electrical fault classification	SVM with RBF kernel	Accuracy, precision, recall	SVM demonstrated strong capability for electrical fault classification	Performance depends on kernel and parameter configuration
Yu *et al.* (2024)	Power-quality disturbance data; multiclass	XGBoost with feature extraction	Classification accuracy and efficiency	XGBoost provided effective classification when combined with appropriate feature extraction	Performance depends on feature representation
Awalin *et al.* (2025)	Current and voltage characteristics; multiple fault types	Rule-based fault classification	Classification accuracy	Effective classification was obtained under several fault conditions	Performance becomes more challenging under complex networks and high-resistance faults
Anwar *et al.* (2025)	Multiple electrical fault categories	Machine-learning/ensemble approach	Accuracy and multiclass performance	Data-driven classification improved discrimination among multiple fault categories	Similar signal patterns among classes remain a classification challenge
Yasin *et al.* (2026)	Three-phase current, voltage, and engineered features; Normal vs Fault	ANN, RF, SVM, Logistic Regression	Accuracy, AUC, precision, recall, F1-score, robustness and calibration	ANN achieved AUC 0.987 and accuracy ≈ 98.5%; RF provided the best comparative performance	Limited to binary classification and did not distinguish specific fault types
Present Study	7,861 observations; Ia, Ib, Ic, Va,	Random Forest, SVM, XGBoost	Accuracy, precision, recall, F1-score, 5-fold	Reported in Results and Discussion	Focuses on structured current and

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	Vb, Vc; Normal, LG, LL, LLG, LLL, LLLG	stratified CV, confusion matrix, feature importance	voltage features from a secondary dataset

As summarized in Table 1, previous studies have demonstrated the effectiveness of various machine learning and signal-processing approaches for electrical fault detection and classification. However, differences in classification scope, feature representation, datasets, and evaluation strategies make direct performance comparisons across studies challenging. In particular, previous work by Yasin *et al*. (2026) demonstrated strong performance for binary fault detection but did not distinguish specific fault categories, thereby limiting the diagnostic information provided. Building on these findings, the present study extends the classification task to six operating conditions (Normal, LG, LL, LLG, LLL, and LLLG) and evaluates Random Forest, SVM, and XGBoost under a consistent experimental framework. In addition to conventional performance metrics, the study incorporates cross-validation, confusion-matrix analysis, and feature importance to examine model stability, class-level misclassification, and the relative contribution of current and voltage features.

2.3 Positioning Your Research

Although machine learning has demonstrated strong potential for electrical fault detection and classification, an important gap remains between detecting the presence of a fault and identifying its specific type. Yasin *et al*. (2026) successfully distinguished normal and fault conditions but did not differentiate specific fault categories, thereby limiting the diagnostic information provided. Multiclass fault classification introduces greater complexity because different fault types may exhibit similar current and voltage characteristics (Nandhini & Prajith, 2023). Moreover, overall accuracy alone may not adequately reveal class-specific errors or model stability. Accordingly, the present study is positioned as an extension from binary fault detection toward multiclass fault diagnosis, with emphasis on identifying specific fault categories and providing a more comprehensive evaluation of classification performance.

2.4 Review of Technologies, Frameworks, and Algorithms

The present study extends binary fault detection toward six-class classification comprising Normal, LG, LL, LLG, LLL, and LLLG conditions. Using six electrical features (Ia, Ib, Ic, Va, Vb, and Vc), Random Forest, SVM, and XGBoost are evaluated under a consistent experimental framework to enable a balanced comparison of their classification performance. The models are assessed using accuracy, precision, recall, and F1-score, complemented by five-fold stratified cross-validation to examine performance stability (Agarwal *et al*., 2024; Nurul'aini *et al*., 2025). In addition, confusion-matrix and feature-importance analyses are incorporated to examine class-specific errors and the relative contribution of electrical features (Singla *et al*., 2024; Xin *et al*., 2025). This methodological framework positions the study beyond fault-presence detection by integrating multiclass diagnosis, comparative model evaluation, stability assessment, and model interpretation. The novelty of this study lies not in introducing a new machine learning algorithm, but in integrating multiclass fault identification, comparative model evaluation, stability assessment, feature interpretation, and class-level misclassification analysis within a unified framework. This approach extends previous binary fault-detection research toward more informative fault diagnosis and provides additional insight into both model performance and the electrical characteristics associated with classification difficulty.

3. Methodology

This study employed a quantitative experimental approach to classify electrical faults in a three-phase power system using Random Forest (RF), Support Vector Machine (SVM), and XGBoost. The research procedure consisted of dataset preparation, preprocessing, model training, performance evaluation, cross-validation, and model interpretation. All classifiers were evaluated under a consistent experimental setting to ensure a fair comparison of their multiclass classification performance. The overall research framework is illustrated in Figure 1.

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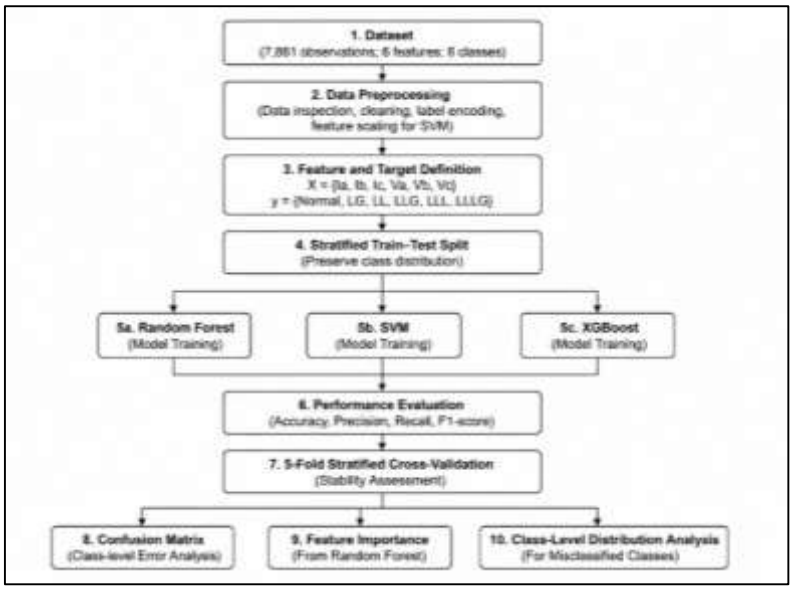


Figure 1. Research Framework for Multiclass Electrical Fault Classification

3.1 Dataset and Preprocessing

This study used the publicly available Electrical Fault Detection and Classification dataset obtained from the Kaggle repository. The dataset comprised 7,861 observations and ten original variables, including four binary fault indicators (G, C, B, and A) and six electrical measurements consisting of three-phase currents (Ia, Ib, and Ic) and three-phase voltages (Va, Vb, and Vc). The four binary indicators were used to derive six operating-condition labels: Normal, Line-to-Ground (LG), Line-to-Line (LL), Double Line-to-Ground (LLG), Three-Phase (LLL), and Three-Phase-to-Ground (LLLG) faults. The six current and voltage measurements were subsequently used as predictor variables. Data preprocessing included data-quality inspection, feature and target separation, class-label construction, and stratified data partitioning. No missing values were identified in the 7,861 observations. The dataset was divided into 80% training data and 20% testing data using stratified sampling with a random seed of 42, thereby preserving the class distribution in both subsets. The resulting partition consisted of 6,288 training observations and 1,573 independent test observations. Feature standardization was applied to SVM because its decision function is sensitive to differences in feature scales, whereas Random Forest and XGBoost were trained using the original feature scales.

3.2 Classification Models

Three machine learning algorithms were comparatively evaluated in this study. Random Forest employs an ensemble of decision trees and was selected for its ability to model nonlinear relationships and provide feature-importance information. SVM constructs optimal decision boundaries between classes and was applied to standardized electrical features. XGBoost employs sequential gradient-boosted decision trees to progressively reduce classification errors. All three models were trained and evaluated using the same data partition to maintain experimental consistency.

3.3 Experimental Setup and Evaluation

The classification experiments were conducted using a consistent experimental setting to ensure a fair comparison among Random Forest, SVM, and XGBoost. As described in Section 3.1, the same 80:20 stratified data partition and feature scaling strategies were applied across all classifiers. The main experimental settings and model configurations are summarized in Table 2.

Table 2. Experimental Configuration and Hyperparameter Settings

Component	Configuration / Setting
Dataset	Electrical Fault Detection and Classification
Total observations	7,861
Predictor features	Ia, Ib, Ic, Va, Vb, Vc
Number of classes	6 (Normal, LG, LL, LLG, LLL, LLLG)
Train-test split	80:20
Training observations	6,288
Testing observations	1,573
Sampling strategy	Stratified train-test split
Random seed	42

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Random Forest	Baseline configuration
SVM	Standardized features; baseline configuration
XGBoost	Baseline configuration
Cross-validation	5-fold stratified cross-validation
Evaluation metrics	Accuracy, weighted precision, weighted recall, weighted F1-score
RF hyperparameter tuning	To be verified from the experimental procedure
Hyperparameter search space	To be verified
Tuning data	Training data only
Test-set utilization	Final evaluation only
Class-imbalance handling	Stratified sampling and weighted evaluation metrics
Software environment	To be verified
Main libraries	To be verified

Note. Source: Authors' experimental configuration (2026)

Model performance was evaluated using accuracy, weighted precision, weighted recall, and weighted F1-score. Weighted metrics were employed to account for the moderate class imbalance in the dataset, particularly because the Normal class contained a larger proportion of observations than each individual fault class. Stratified sampling was also applied to preserve the original class proportions in both the training and testing subsets. These evaluation metrics enabled comparison of overall predictive performance while accounting for differences in class frequencies. In addition to hold-out testing, five-fold stratified cross-validation was performed to assess model stability and generalization across different data partitions. Stratification ensured that the relative distribution of the six operating-condition classes was maintained within each fold. Model stability was evaluated using the mean and standard deviation of accuracy and F1-score across the five folds. This complementary validation procedure reduced reliance on a single train-test partition and provided a more robust assessment of comparative model performance.

3.4 Model Interpretation

Model interpretation was conducted using Random Forest feature importance and class-level feature-distribution analysis. The feature-importance scores were used to quantify the global relative contribution of the six electrical features (Ia, Ib, Ic, Va, Vb, and Vc) to the Random Forest classification process. These scores were interpreted as measures of overall feature contribution across all operating conditions rather than as class-specific indicators. Therefore, global feature importance was not used to directly explain the misclassification between individual fault-class pairs. To investigate class-specific classification difficulty, the distributions of the current and voltage features were separately examined for fault classes exhibiting substantial reciprocal misclassification in the confusion matrices. In particular, the LLL and LLLG classes were compared because these classes showed the most persistent confusion across the evaluated classifiers. The distribution analysis was used to assess the extent of overlap in their electrical measurements and to provide complementary evidence regarding their limited separability. By combining global feature importance with class-level distribution analysis while maintaining their distinct interpretations, the study provides a more cautious and methodologically appropriate assessment of model behavior.

4. Results and Discussion

4.1 Results

4.1.1 Dataset Characteristics and Class Distribution

The dataset used in this study consisted of 7,861 observations representing normal and fault conditions in a three-phase electrical power system. Six numerical features were used as predictors, comprising three-phase current measurements (Ia, Ib, and Ic) and three-phase voltage measurements (Va, Vb, and Vc). Initial data-quality inspection confirmed that all 7,861 observations contained complete values for the predictor variables, with no missing values identified. The classification target comprised six operating conditions: Normal, Line-to-Ground (LG), Line-to-Line (LL), Double Line-to-Ground (LLG), Three-Phase (LLL), and Three-Phase-to-Ground (LLLG) faults. The class distribution showed that the Normal condition contained the largest number of observations, with 2,365 samples (30.09%). Among the fault classes, LLG contained 1,134 samples (14.43%), LLLG contained 1,133 samples (14.41%), LG contained 1,129 samples (14.36%), LLL contained 1,096 samples (13.94%), and LL contained 1,004 samples (12.77%). Although the Normal class was more prevalent than each individual fault class, the five fault categories showed relatively comparable proportions, ranging from 12.77% to 14.43%. The complete class distribution is presented in Table 3.

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Table 3. Distribution of Electrical Fault Classes

Fault Class	Samples	Percentage (%)
Normal	2,365	30.09
LG	1,129	14.36
LL	1,004	12.77
LLG	1,134	14.43
LLL	1,096	13.94
LLLG	1,133	14.41
Total	7,861	100.00

Note. Source: Authors' calculation (2026).

As shown in Table 3, the dataset exhibited moderate class imbalance, primarily because the Normal class accounted for approximately 30% of the observations, whereas each individual fault class represented approximately 13–14%. However, the five fault categories themselves were relatively balanced. To account for this distribution, stratified sampling was employed during the 80:20 train-test partition to preserve class proportions across the training and testing subsets. In addition, weighted precision, recall, and F1-score were used in model evaluation to account for differences in class frequencies. These procedures provided a consistent basis for comparing Random Forest, SVM, and XGBoost under the same class-distribution conditions.

4.1.2 Descriptive Analysis of Electrical Features

Descriptive analysis was conducted to examine the statistical characteristics and relationships among the six electrical features used for fault classification. The current features (Ia, Ib, and Ic) exhibited substantial variation across the observations, reflecting changes in phase-current behavior under different operating and fault conditions. Variations were also observed in the voltage features (Va, Vb, and Vc), indicating that both current and voltage measurements contained potentially relevant information for distinguishing the six operating conditions. Correlation analysis was subsequently performed to examine the relationships among the six predictor variables. The resulting correlation matrix revealed varying degrees of association among the current and voltage features rather than uniformly strong correlations. This pattern indicates that the variables capture complementary aspects of the three-phase electrical system and supports retaining all six features for subsequent classification. The correlation structure among Ia, Ib, Ic, Va, Vb, and Vc is presented in Figure 2.



Figure 2. Correlation Matrix of Three-Phase Current and Voltage Features

As illustrated in Figure 2, no uniformly strong correlation pattern was observed across all six electrical features. Instead, the current and voltage variables exhibited heterogeneous relationships, suggesting that individual features provide complementary information for the classification task. Retaining all six variables therefore enabled the evaluated machine learning models to capture multivariate patterns associated with the different operating and fault conditions.

4.1.3 Classification Performance

The classification performance of Random Forest, SVM, and XGBoost was evaluated on the independent test set using accuracy, weighted precision, weighted recall, and weighted F1-score. In addition to the three

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baseline classifiers, the tuned Random Forest model was evaluated to determine whether hyperparameter optimization improved predictive performance. All models were evaluated using the same test partition to ensure a consistent comparison. The results are presented in Table 4.

Table 4. Performance Comparison of Classification Models

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	0.8678	0.8675	0.8678	0.8676
SVM	0.8099	0.8087	0.8099	0.8081
XGBoost	0.7978	0.7975	0.7978	0.7976
Tuned Random Forest	0.8659	0.8650	0.8659	0.8654

Note. Source: Authors' calculation (2026).

As shown in Table 4, the baseline Random Forest achieved the highest overall test-set performance, with an accuracy of 0.8678 and a weighted F1-score of 0.8676. SVM ranked second, achieving an accuracy of 0.8099 and an F1-score of 0.8081, whereas XGBoost produced an accuracy of 0.7978 and an F1-score of 0.7976. These results indicate that Random Forest provided the strongest predictive performance among the three baseline classifiers under the same experimental conditions. Hyperparameter optimization did not improve the performance of Random Forest on the independent test set. The tuned Random Forest achieved an accuracy of 0.8659 and an F1-score of 0.8654, slightly below the baseline Random Forest values of 0.8678 and 0.8676, respectively. The difference was small, indicating that parameter optimization did not provide an additional test-set performance advantage under the investigated configuration. Accordingly, the baseline Random Forest was retained as the best-performing model for subsequent class-level and feature-importance analyses.

4.1.4 Cross-Validation and Model Stability

To assess model stability and generalization beyond a single hold-out partition, five-fold stratified cross-validation was performed for Random Forest, SVM, and XGBoost. Stratification preserved the relative distribution of the six operating-condition classes within each fold. Model performance was summarized using the mean and standard deviation of accuracy and weighted F1-score across the five folds. The cross-validation results are presented in Table 5.

Table 5. Five-Fold Stratified Cross-Validation Results

Model	Accuracy Mean	Accuracy SD	F1 Mean	F1 SD
Random Forest	0.8755	0.0045	0.8753	0.0047
SVM	0.8049	0.0033	0.8000	0.0037
XGBoost	0.8021	0.0035	0.8017	0.0036

Note. Source: Authors' calculation (2026).

As shown in Table 5, Random Forest achieved the highest mean cross-validation accuracy of 0.8755 and the highest mean F1-score of 0.8753. SVM achieved a mean accuracy of 0.8049 and a mean F1-score of 0.8000, while XGBoost produced corresponding values of 0.8021 and 0.8017. These results are consistent with the hold-out evaluation reported in Table 4, in which Random Forest also achieved the highest overall predictive performance.

4.1.5 Class-Level Misclassification Analysis

To further examine model performance at the class level, confusion matrices were analyzed for Random Forest, SVM, and XGBoost using the independent test set of 1,573 observations. Unlike aggregate performance metrics, confusion-matrix analysis provides detailed information on correctly classified and misclassified observations for each operating condition. The class totals represented in the confusion matrices correspond to the stratified 20% test partition described in Section 3.1. The confusion matrices for the three classifiers are presented in Figures 3–5.

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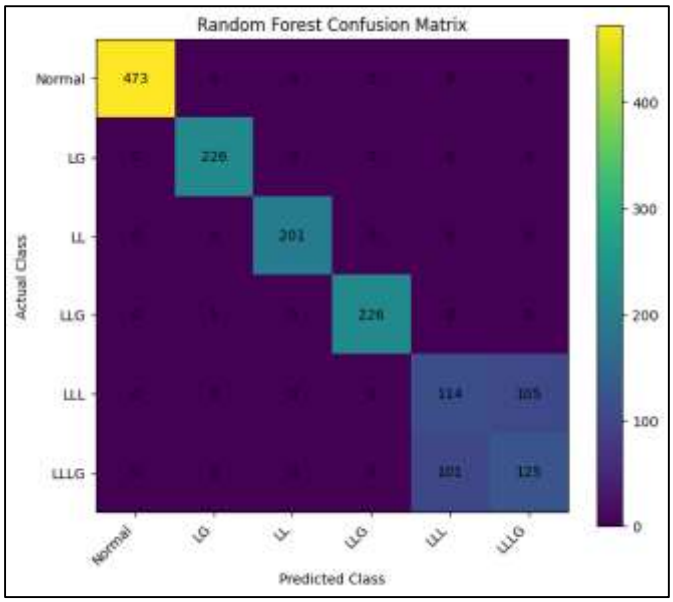


Figure 3. Confusion Matrix of the Random Forest Model

Note. Source: Authors' calculation (2026).

As shown in Figure 3, Random Forest correctly classified all Normal (473), LG (226), and LL (201) samples, while 226 of 227 LLG samples were correctly identified. The principal classification errors occurred between the LLL and LLLG classes. Of the 219 LLL samples, 114 were correctly classified, while 105 were misclassified as LLLG. Similarly, of the 227 LLLG samples, 125 were correctly classified, while 101 were misclassified as LLL. Considering both correctly classified and misclassified observations, the class totals across the confusion matrix sum to 1,573 test samples, consistent with the 20% hold-out test partition. These results identify reciprocal misclassification between LLL and LLLG as the primary source of error for the Random Forest model.

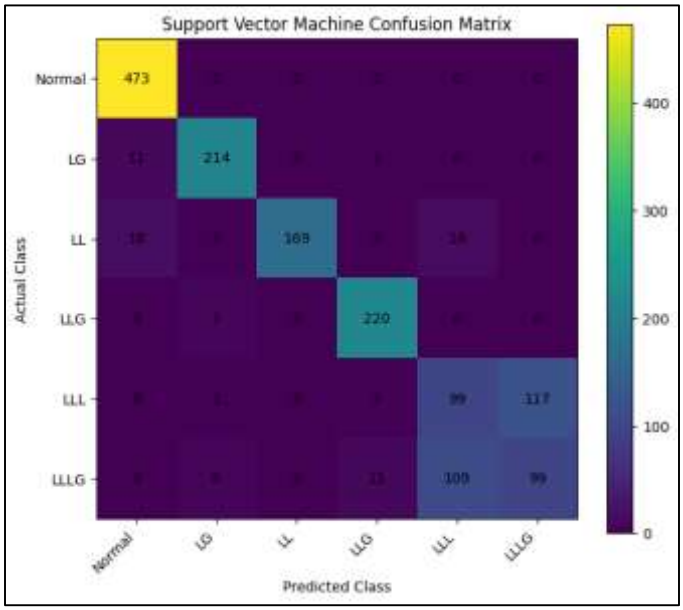


Figure 4. Confusion Matrix of the Support Vector Machine Model

Note. Source: Authors' calculation (2026).

As shown in Figure 4, SVM correctly classified all 473 Normal samples, while 214 of 226 LG samples, 169 of 201 LL samples, and 220 of 227 LLG samples were correctly identified. Greater classification difficulty was observed for the LLL and LLLG classes. Of the 219 LLL samples, 99 were correctly classified, while 117 were misclassified as LLLG. For the LLLG class, 99 of 227 samples were correctly classified, while 109 were misclassified as LLL. These reciprocal errors indicate that distinguishing LLL from LLLG remained the principal class-level challenge for SVM.

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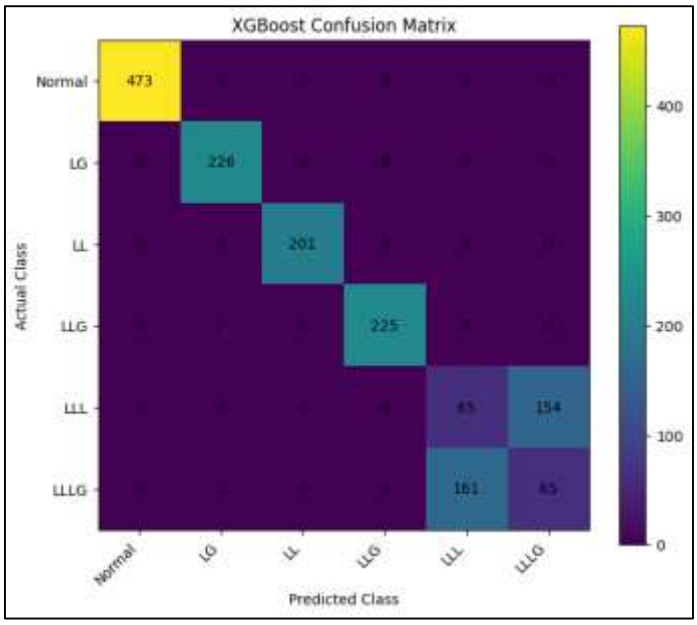


Figure 5. Confusion Matrix of the XGBoost Model

Note. Source: Authors' calculation (2026).

As shown in Figure 5, XGBoost correctly classified all Normal (473), LG (226), and LL (201) samples, while 225 of 227 LLG samples were correctly identified. However, substantial reciprocal misclassification occurred between LLL and LLLG. Only 65 of 219 LLL samples were correctly classified, while 154 were misclassified as LLLG. Similarly, 65 of 227 LLLG samples were correctly identified, while 161 were misclassified as LLL. Compared with Random Forest, XGBoost therefore exhibited greater difficulty in separating these two fault classes, which contributed to its lower overall classification performance. Collectively, the three confusion matrices reveal a consistent class-level pattern. Normal, LG, LL, and LLG were classified with relatively high reliability, whereas LLL and LLLG exhibited substantial reciprocal misclassification across all three classifiers. Because this pattern persisted across different learning algorithms, further analysis was conducted to examine whether the available electrical features exhibited overlapping distributions between these two difficult-to-distinguish fault classes.

4.1.6 Feature Importance and Difficult-Class Analysis

To further interpret the behavior of the best-performing model, global feature-importance analysis was conducted using Random Forest. The analysis quantified the relative contribution of each current and voltage feature to the overall multiclass classification process. Importantly, these feature-importance values represent global contributions across all six operating conditions and were not interpreted as direct measures of class-specific separability. The resulting feature-importance values are presented in Figure 6.

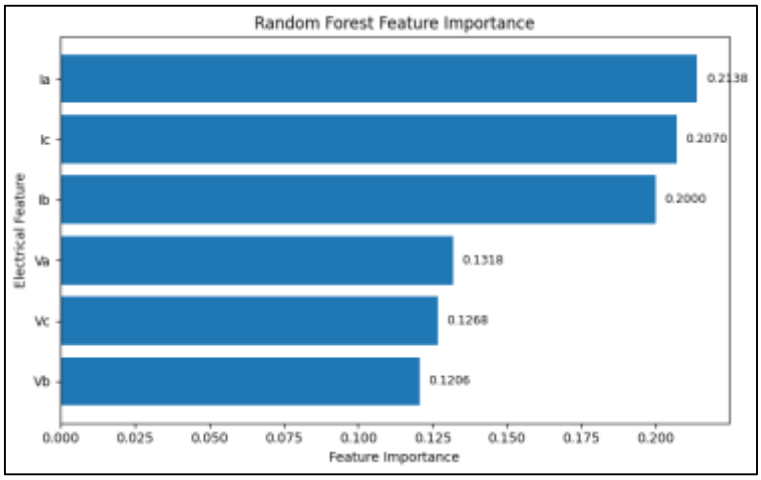


Figure 6. Random Forest Feature Importance

Note. Source: Authors' calculation (2026).

As shown in Figure 6, the three current features received the highest global importance scores in the Random Forest model. Ia had the highest importance value (0.2138), followed by Ic (0.2070) and Ib (0.2000). The

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voltage features showed lower global importance values, with Va, Vc, and Vb obtaining scores of 0.1318, 0.1268, and 0.1206, respectively. These results indicate that current measurements contributed more strongly than voltage measurements to the overall Random Forest classification process across all six classes. However, because these importance scores are global, they do not by themselves explain the specific reciprocal misclassification observed between LLL and LLLG. To investigate the class-specific difficulty identified in the confusion-matrix analysis, a separate distributional analysis was conducted for the LLL and LLLG classes. These two classes were selected because substantial reciprocal misclassification was consistently observed across Random Forest, SVM, and XGBoost. Unlike global feature importance, this analysis directly examined the distributions of the electrical measurements within the two difficult-to-distinguish classes. The distributions of the three current features are presented in Figure 7.

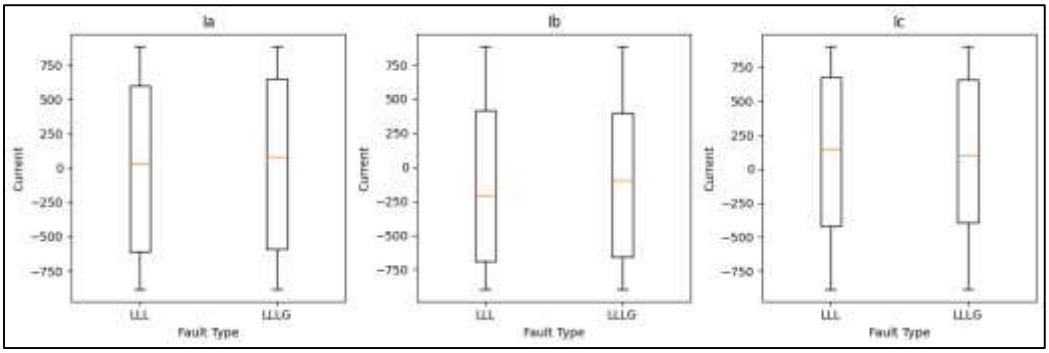


Figure 7. Distribution of Current Features for LLL and LLLG Fault Classes

Note. Source: Authors' calculation (2026).

As shown in Figure 7, the distributions of Ia, Ib, and Ic exhibited substantial overlap between the LLL and LLLG fault classes. Although some differences in median values were observed, particularly for Ia and Ib, the overall ranges and interquartile distributions remained highly similar. This distributional overlap provides class-specific evidence that the available current measurements offer limited separation between LLL and LLLG, consistent with the reciprocal misclassification observed in the confusion matrices. In addition to the current measurements, the distributions of the voltage features were examined to determine whether Va, Vb, and Vc provided clearer separation between LLL and LLLG. The corresponding voltage distributions are presented in Figure 8.

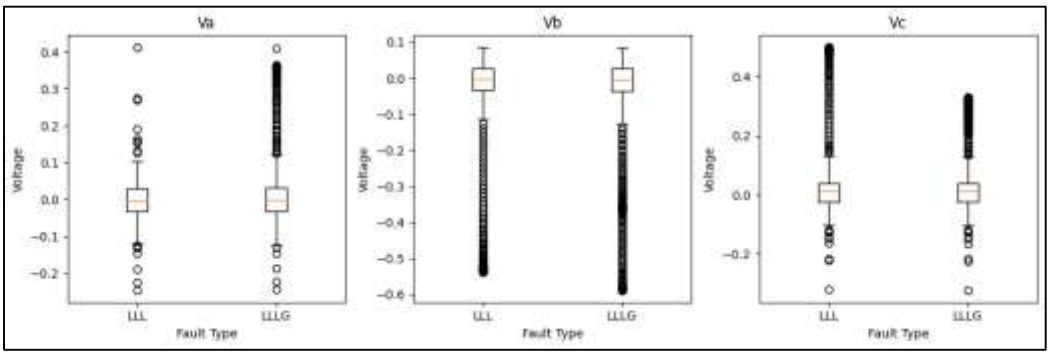


Figure 8. Distribution of Voltage Features for LLL and LLLG Fault Classes

Note. Source: Authors' calculation (2026).

As shown in Figure 8, Va, Vb, and Vc also exhibited substantial distributional overlap between the LLL and LLLG classes. Their median values and interquartile ranges were relatively similar, although some differences were observed in the distributions of extreme values. These results indicate that the available voltage measurements also provide limited class-specific separation between the two fault conditions. Together with the current-feature distributions in Figure 7, this finding provides direct evidence of substantial feature overlap between LLL and LLLG. Overall, the two complementary analyses provide different levels of interpretation. Random Forest feature importance indicates the global contribution of each electrical variable to multiclass classification, with current features receiving higher overall importance than voltage features. In contrast, the class-level distribution analysis specifically demonstrates substantial overlap in both current and voltage measurements between LLL and LLLG. Therefore, the persistent confusion between these two classes should be attributed to the observed similarity of their feature distributions rather than inferred directly from the global Random Forest feature-importance scores. This distinction provides a more cautious interpretation of model behavior and avoids attributing class-specific separability to a global importance measure.

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4.2 Discussion

The experimental results demonstrate that Random Forest achieved the highest predictive performance among the evaluated classifiers for multiclass electrical fault classification. On the independent test set, Random Forest achieved an accuracy of 0.8678 and a weighted F1-score of 0.8676, compared with accuracies of 0.8099 and 0.7978 for SVM and XGBoost, respectively. The same performance pattern was observed under five-fold stratified cross-validation, where Random Forest achieved the highest mean accuracy of 0.8755 and mean F1-score of 0.8753. Although its fold-to-fold variability was slightly higher than that of SVM and XGBoost, the standard deviations remained low, indicating that its comparatively high predictive performance was maintained across different stratified data partitions. The superior numerical performance of Random Forest in this dataset may be associated with its ensemble structure, which combines multiple decision trees and can capture nonlinear interactions among three-phase current and voltage measurements. In contrast, SVM relies on decision boundaries in the transformed feature space, while XGBoost sequentially constructs boosted trees to reduce prediction errors. The differences observed among the three classifiers therefore reflect their distinct learning mechanisms when applied to the same six-feature multiclass dataset. Importantly, these findings should be interpreted within the experimental conditions of the present study rather than as evidence that Random Forest is universally superior for electrical fault classification. At the class level, the confusion-matrix analysis revealed a more specific classification challenge that was not apparent from the aggregate performance metrics. Normal, LG, LL, and LLG were classified with relatively high reliability, whereas substantial reciprocal misclassification occurred between LLL and LLLG across all three classifiers. For Random Forest, 105 of 219 LLL observations were classified as LLLG, while 101 of 227 LLLG observations were classified as LLL. Similar reciprocal errors were observed for SVM and were even more pronounced for XGBoost. The persistence of this pattern across different learning algorithms suggests that the difficulty is related not only to classifier selection but also to the limited separability of LLL and LLLG using the available six electrical measurements. The model-interpretation results provide complementary, but distinct, insights into this classification behavior. Random Forest assigned higher global feature-importance scores to the current measurements, particularly Ia (0.2138), Ic (0.2070), and Ib (0.2000), than to the voltage measurements. These values indicate that the current features contributed more strongly to the Random Forest classification process across all six classes. However, global feature importance does not measure the separability of a specific pair of classes and therefore should not be interpreted as a direct explanation for the LLL–LLLG confusion. Instead, the class-specific distribution analysis provides the relevant evidence for examining this particular classification difficulty.

The distributional analysis showed substantial overlap between LLL and LLLG in both current and voltage measurements. The distributions of Ia, Ib, and Ic exhibited similar ranges and interquartile patterns between the two classes, while Va, Vb, and Vc also showed considerable overlap. These class-specific findings provide a more direct explanation for the persistent reciprocal misclassification observed in the confusion matrices. Thus, although current measurements were globally more influential in the Random Forest model, the six available electrical features did not provide sufficient class-specific separation to reliably distinguish LLL from LLLG in all observations. These findings clarify the contribution of the present study relative to previous fault-classification research. The contribution does not lie in proposing a new machine learning algorithm, but in evaluating three established classifiers within a consistent multiclass experimental framework that combines hold-out evaluation, stratified cross-validation, class-level confusion analysis, and complementary model-interpretation procedures. This integrated evaluation makes it possible to distinguish between overall model performance, model stability, global feature contribution, and class-specific classification difficulty. Consequently, the study provides more detailed diagnostic information than binary normal-versus-fault detection and avoids relying solely on aggregate accuracy when evaluating multiclass fault-classification performance. The results also extend the binary fault-detection framework discussed in previous work by demonstrating that accurate identification of the presence of a fault does not necessarily imply equally reliable discrimination among individual fault types. While previous binary approaches primarily distinguish Normal from Fault conditions, the present six-class formulation exposes classification difficulties that would otherwise remain hidden, particularly the substantial overlap between LLL and LLLG. This distinction is practically relevant because multiclass diagnosis requires not only detecting an abnormal operating condition but also identifying the specific fault category to provide more informative diagnostic support. Nevertheless, the findings should be interpreted within the scope of the experimental design. The analysis was based on a single secondary dataset containing 7,861 observations and six current and voltage features. Although stratified hold-out testing and five-fold cross-validation were used to evaluate model performance and stability, the dataset may not represent the full range of fault locations, fault resistances, loading conditions, noise levels, and network configurations encountered in operational power systems. Furthermore, the persistent LLL–LLLG overlap indicates that improvements in classifier complexity alone may be insufficient when the available features provide limited class separability. Future studies should therefore investigate additional signal-derived features, signal-processing representations, and validation using more diverse or real-world electrical measurements.

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5. Conclusion and Recommendations

This study evaluated Random Forest, Support Vector Machine (SVM), and XGBoost for multiclass electrical fault classification in a three-phase power system using six electrical features: Ia, Ib, Ic, Va, Vb, and Vc. Under the investigated experimental conditions, Random Forest achieved the highest test-set performance, with an accuracy of 0.8678 and a weighted F1-score of 0.8676, compared with SVM and XGBoost. Five-fold stratified cross-validation produced a mean accuracy of 0.8755 and a mean F1-score of 0.8753 for Random Forest, with relatively low variability across folds. Hyperparameter tuning did not improve its test-set performance, as the tuned Random Forest achieved an accuracy of 0.8659 and an F1-score of 0.8654. These results indicate that the baseline Random Forest provided the highest numerical performance among the evaluated model configurations. Beyond aggregate performance, the class-level analysis revealed substantial differences in classification difficulty. Normal, LG, LL, and LLG were classified with relatively high reliability, whereas LLL and LLLG exhibited persistent reciprocal misclassification across Random Forest, SVM, and XGBoost. Random Forest feature-importance analysis showed that Ia, Ic, and Ib had the highest global importance values of 0.2138, 0.2070, and 0.2000, respectively. However, these global importance scores should not be interpreted as direct explanations of the LLL–LLLG confusion. Instead, the class-specific distribution analysis demonstrated substantial overlap in both current and voltage measurements between LLL and LLLG, indicating limited separability of these two classes using the available six electrical features. The contribution of this study lies in extending electrical fault analysis toward a consistent six-class evaluation framework that integrates hold-out testing, stratified cross-validation, class-level confusion analysis, global feature importance, and class-specific feature-distribution analysis. This framework provides complementary information on predictive performance, stability, feature contribution, and difficult-to-distinguish fault categories. Nevertheless, the findings are limited to a single secondary dataset containing 7,861 observations and six electrical measurements. Therefore, the reported performance should be interpreted within the characteristics of this dataset and should not be generalized directly to all three-phase power-system configurations. Future research should evaluate the classifiers using larger and more diverse datasets covering different fault locations, fault resistances, loading conditions, noise levels, and power-system configurations. Additional signal-derived and time-frequency features may be investigated to improve the separability of LLL and LLLG faults. Future studies may also compare advanced ensemble and deep-learning architectures with the conventional machine-learning models evaluated in this study. Most importantly, validation using real-world electrical measurements is recommended to assess model robustness, generalizability, and practical applicability under operational power-system conditions.

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