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Machine Learning-Based Intelligent Fault Detection and Classification in Power Networks

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ABSTRACT
Power system faults, including ground disturbances and short circuits, pose a substantial hazard to the reliability of electrical power systems, which are considered critical infrastructure. It is imperative to maintain system stability and minimize service interruptions by rapidly and precisely identifying and classifying faults. This paper proposes a durable framework for real-time fault detection and multi-class classification in electrical power grids, powered by AI-driven models trained via supervised learning. To produce exhaustive datasets of three-phase voltage and current signals under a variety of fault and normal operating conditions, an IEEE 5-bus power system is modelled and simulated in MATLAB/Simulink. These measurements are processed and used as input features for a variety of classifiers, including Random Forest, Support Vector Machine, Decision Tree, and Logistic Regression. Model performance is assessed for both binary and multi-class classification tasks by analyzing the confusion matrix, accuracy, along with precision, recall, and F1-score. Experimental results demonstrate that the Random Forest classifier consistently outperforms other models. It exhibits high robustness to noise and strong capacity to capture the behavior of nonlinear systems. The increasing availability of high-resolution measurement data from modern monitoring infrastructure further enhances the applicability of machine learning–based fault diagnosis. The proposed framework enables fast, reliable, and scalable fault identification, providing an effective foundation for intelligent protection schemes in modern and future smart grid environments.

Keywords: Power Grid; IEEE 5 bus; Fault Detection; Fault Classification; Machine Learning; Smart Grid.

1. Introduction

Power system faults can be broadly categorized as transient or permanent based on how long the disturbance persists. Transient faults last for very short durations, typically from microseconds to millisecond, and often clear on their own, causing limited immediate impact on system operation. Despite their short duration, they indicate underlying irregularities in system components and should be carefully monitored, as they can develop into permanent faults. Such transient events may be triggered by factors including equipment degradation, variations in load, lightning strikes, or switching operations[1-3]. A specific category of transient disturbance is the incipient fault, which originates internally within the system and occurs over brief intervals ranging from a fraction of a cycle to several cycles, usually with relatively low fault current levels. These faults are commonly associated with the aging of cables, where insulation weakens over time due to electrical stress, mechanical strain, chemical contamination, and environmental influences. If such faults recur, they can eventually evolve into permanent failures in transmission and distribution networks. Continuous real-time observation of pre-fault indicators enables early detection of abnormal system behavior, helping operators anticipate and mitigate the progression toward permanent faults [4][5]. In power systems, permanent faults are grouped into symmetrical and asymmetrical categories based on phase involvement. These include single phase-to-ground faults, faults between two phases, two phases connected to ground, as well as three-phase faults with and without ground connection. Their occurrences are further classified into eleven possibilities depending upon the phases involved, as illustrated in Fig. 1.

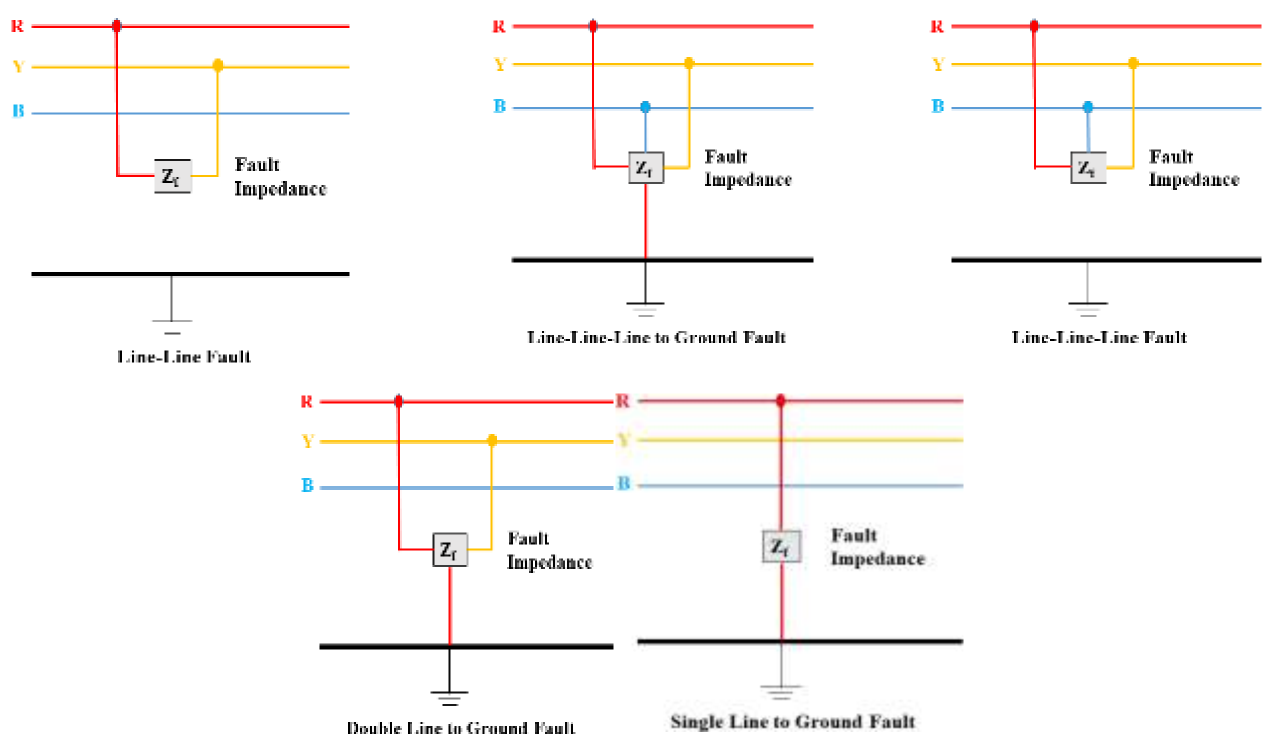

Figure. 1. Illustration of fault scenarios for each type of fault.

The alteration in voltage and current characteristics during the transition from normal to faulty operation is significantly influenced by fault attributes such as fault type, impedance, distance, and inception angle. Figure 1 represents the fault scenarios of each fault type. Where Zf represents the fault impedance. Fault impedance is typically categorized as either high or low impedance faults. High impedance faults pose challenges in fault diagnosis due to their extremely low fault current values. Subsequently, there have been numerous research endeavours that have been especially concentrated on the detection, classification, and localisation of high-impedance faults. To guarantee the power system's reliable operation, it is essential to promptly detect, classify, and localise faults in order to prevent protracted power supply interruptions, cascading failures, and blackouts [7].

1.1 Objectives of the work:

- To develop an efficient machine learning–based framework for accurate fault detection in power grids.
- To design a reliable method for classification of different types of power system faults using data-driven techniques.
- To extract and analyze relevant features from voltage and current signals for improving fault identification accuracy.
- To enhance real-time monitoring and decision-making capability in modern power systems.
- To improve overall grid reliability and fault diagnosis performance through intelligent algorithms.

2. Methods

2.1. Implementation of IEEE 5 Bus System:

This work combines detailed power system simulation with advanced artificial intelligence techniques to develop an intelligent and reliable fault classification framework for electrical power grids. The IEEE 5-bus test network is developed using MATLAB/Simulink, a widely recognized and practical platform for studying system performance under both normal and fault conditions. Multiple fault types—including single phase-to-ground faults, faults between two phases, two phases connected to ground, as well as three-phase faults are introduced at various locations and time instances [8][9][10]. These simulations are used to generate a comprehensive dataset consisting of three-phase voltage and current signals. This simulation-driven approach enables controlled experimentation, repeatability, and accurate labeling of fault conditions, which are essential for supervised machine learning applications.

The generated electrical signals are processed using Python-based machine learning tools. Data preprocessing procedures, including noise filtering, normalization, feature extraction, and dataset structuring, are performed to enhance learning efficiency and model performance. Established libraries, such as Scikit-learn, are employed to train and evaluate machine learning algorithms, thereby guaranteeing the efficient and dependable implementation of classification techniques[11]. The integration of MATLAB/Simulink with Python establishes a robust end-to-end framework that combines accurate physical system modeling with flexible data-driven analysis.

The proposed framework is relevant to power utilities, transmission and distribution operators, protection engineers, and researchers in smart grid technologies. It enables faster and more accurate fault identification, facilitating rapid isolation of faulty sections and reducing the likelihood of cascading failures [12][13][14]. From a broader perspective, the approach improves grid reliability, minimizes equipment damage, reduces outage duration, and supports enhanced decision-making in modern smart grid environments, contributing to safer and more resilient power system operation. The observed waveform variations indicate that each fault condition generates a distinct electrical signature that can be effectively exploited for fault detection and classification. Differences in signal amplitude, phase imbalance, and transient characteristics of voltages and currents provide discriminative features for separating various fault categories. The IEEE 5-bus simulated waveforms are confirmed to be suitable for the development and validation of machine learning-based fault classification models by these findings, as the extracted features faithfully capture the physical effects of various fault conditions on the power system [15]. Overall, the analysis demonstrates that voltage and current waveform characteristics constitute a reliable and informative basis for identifying fault occurrence, type, and severity, thereby enabling faster protective actions and enhancing overall system reliability.

2.2 Proposed AI Framework

The proposed approach is organized as a systematic workflow that includes system modeling, simulation of faults, data collection, preprocessing, training of machine learning models, and evaluation of their performance [16][17]. The input feature vector is given by:

$X = \{V_R, V_Y, V_B, I_R, I_Y, I_B\}$ ……………………………………. (1)

where V_R, V_Y, V_B represent three-phase voltages and I_R, I_Y, I_B represent three-phase currents. The output variable **Y** corresponds to the fault type:

{No Fault, LG, LL, LLG, LLL, LLLG} …………………….. (2)

The objective is to learn a mapping function:

$f(X) \rightarrow Y$………………………………………………………(3)

using machine learning classifiers.

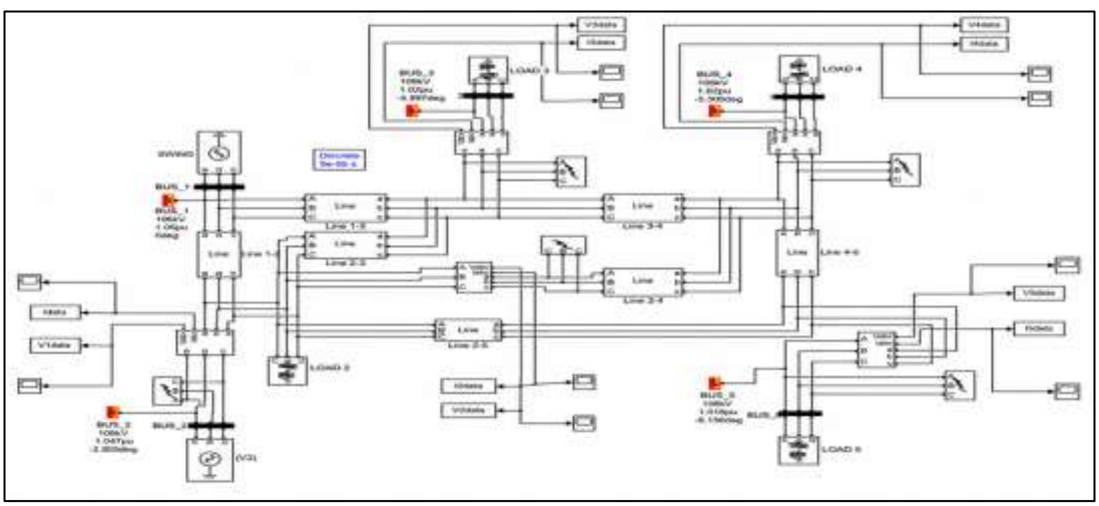

Figure 2. Simulation model of standard 5 Bus System

Figure 2 illustrates the MATLAB/Simulink implementation of the IEEE 5-bus test system employed for fault analysis. The system comprises five buses, transmission lines, generation sources, and loads interconnected to represent a practical power network. Various fault types, including LG, LL, LLG, LLL, and LLLG faults, are introduced using fault blocks, while voltage and current measurement units collect three-phase signals from different buses. The acquired data are exported for preprocessing and utilized in training machine learning models for fault classification.

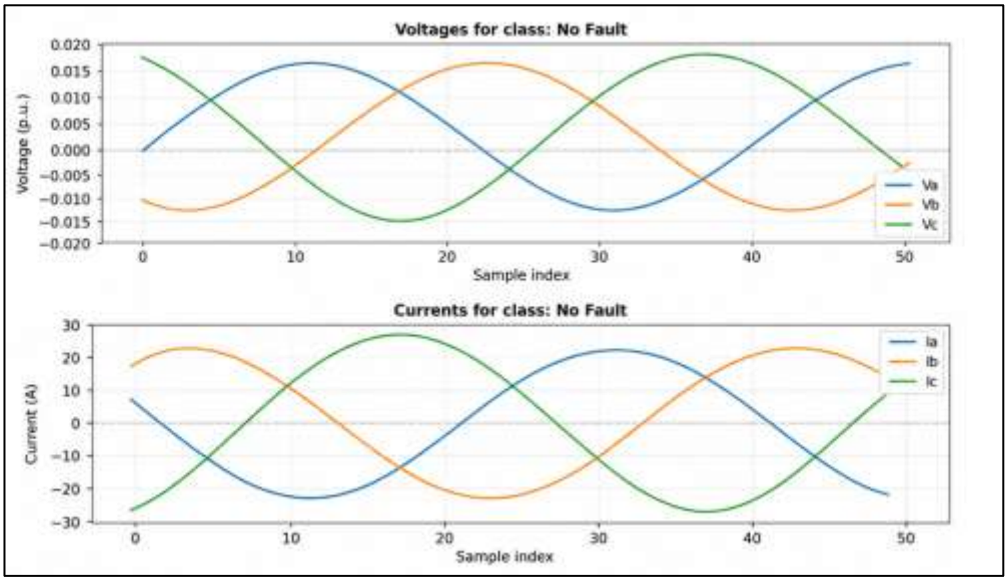

Figure 3. Voltage–current signal patterns under no-fault operating conditions

Figure 3 illustrates the balanced three-phase voltage and current waveforms under no-fault conditions. All phases maintain sinusoidal profiles with equal magnitudes and a 120° phase shift, demonstrating normal and stable system operation. These signals are utilized as baseline patterns for distinguishing healthy and faulty operating states in the proposed fault classification model.

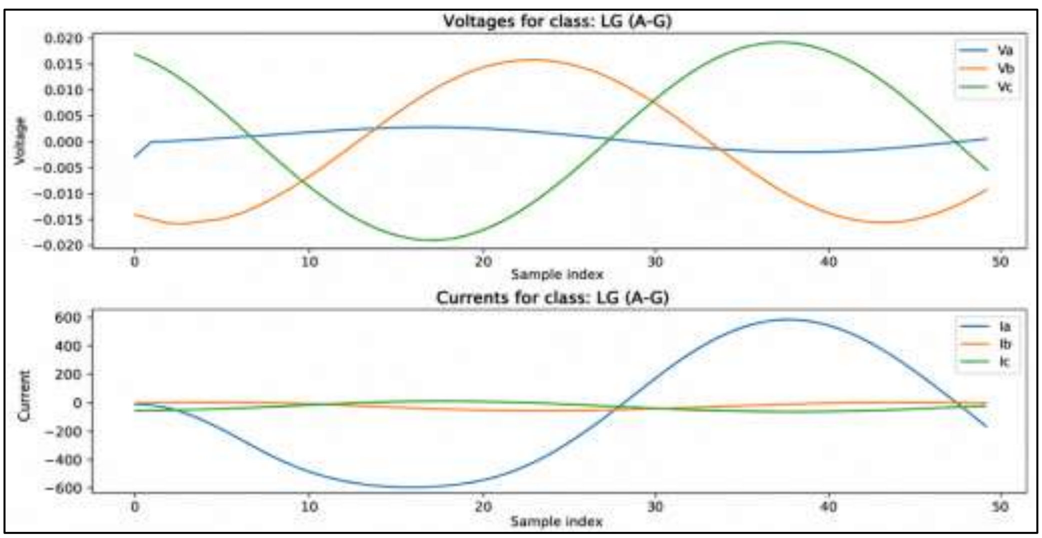

Figure 4. Voltage–current signal patterns under line-to-ground (LG) fault conditions

Figure 4 depicts the voltage and current waveforms under an A–G line-to-ground (LG) fault condition. The faulted phase (A) exhibits a significant voltage sag accompanied by a substantial increase in fault current, whereas the healthy phases maintain nearly sinusoidal voltage profiles with only minor current disturbances. These characteristic signatures facilitate reliable detection and classification of LG faults in power distribution systems.

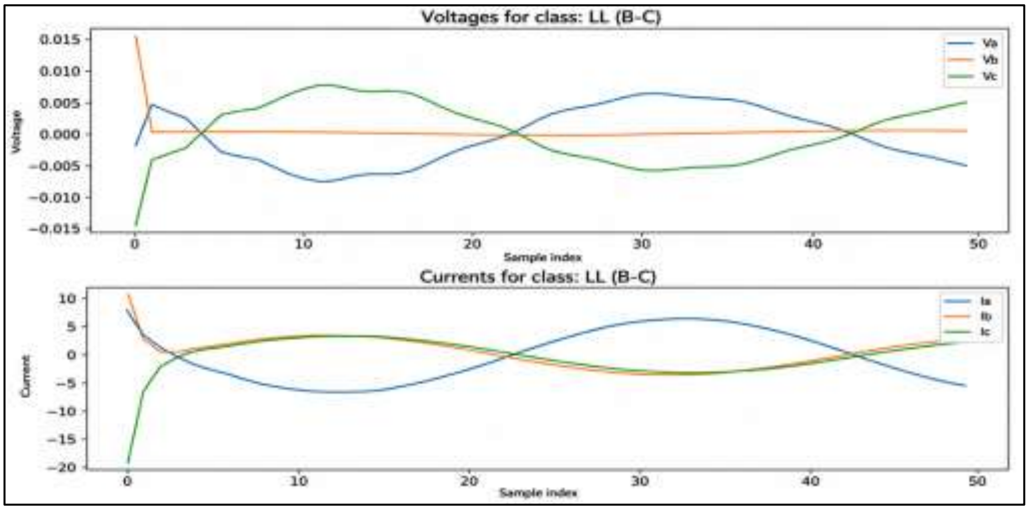

Figure 5. Voltage–current signal patterns behavior during a phase-to-phase fault

Figure 5 illustrates the three-phase voltage and current waveforms under a line-to-line (LL) fault between phases B and C. During the fault, the voltages of the faulted phases (Vb and Vc) exhibit significant deviations from their normal profiles, while the unfaulted phase voltage (Va) remains comparatively less affected. The current waveforms show a substantial increase in the faulted phase currents (Ib and Ic), which flow in opposite directions due to the phase-to-phase short circuit, whereas the current in the healthy phase (Ia) experiences relatively smaller variations. These distinctive voltage and current signatures are characteristic of an LL (B–C) fault and facilitate accurate fault identification and classification in power distribution systems.

Figure 6 presents the three-phase voltage and current waveforms under a double line-to-ground (LLG: B–C–G) fault condition. The fault causes significant disturbances in the voltages and currents of the affected phases (B and C), accompanied by a ground return path that results in elevated fault current magnitudes. In contrast, the unfaulted phase (A) exhibits comparatively smaller deviations. The unbalanced voltage and current patterns observed are characteristic signatures of an LLG fault and can be effectively utilized for fault detection and classification in power distribution networks.

Figure 7 depicts the three-phase voltage and current waveforms under a three-phase (LLL) fault condition. The fault results in a simultaneous collapse of all phase voltages to nearly zero, indicating a balanced short-circuit involving all three phases. Correspondingly, the phase currents attain significantly high magnitudes while remaining nearly balanced and phase-shifted by 120°, reflecting the symmetrical nature of the fault. These distinctive characteristics serve as reliable indicators for the detection and classification of three-phase faults in power distribution systems.

Figure 8 illustrates the three-phase voltage and current waveforms under a three-phase-to-ground (LLLG) fault condition. The fault causes severe disturbances in the system, resulting in substantial fault currents in all three phases due to the direct connection of the phases to ground. Although the voltage waveforms remain balanced, the current waveforms exhibit a sudden increase in magnitude at the fault inception, indicating the symmetrical and highly severe nature of the LLLG fault. These distinctive characteristics provide effective features for the detection and classification of three-phase-to-ground faults in power distribution systems.

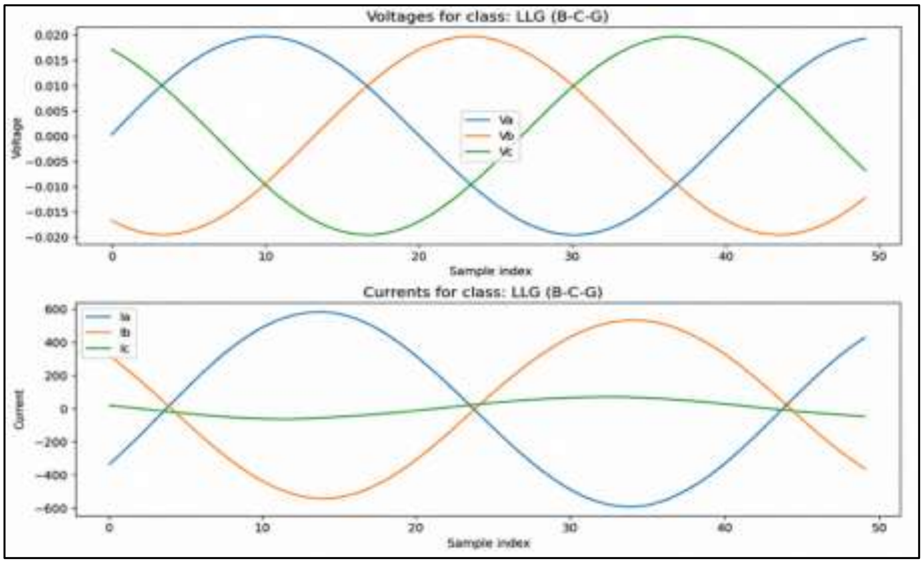

Figure 6. Voltage–current signal patterns behavior during a two-phase-to-ground fault

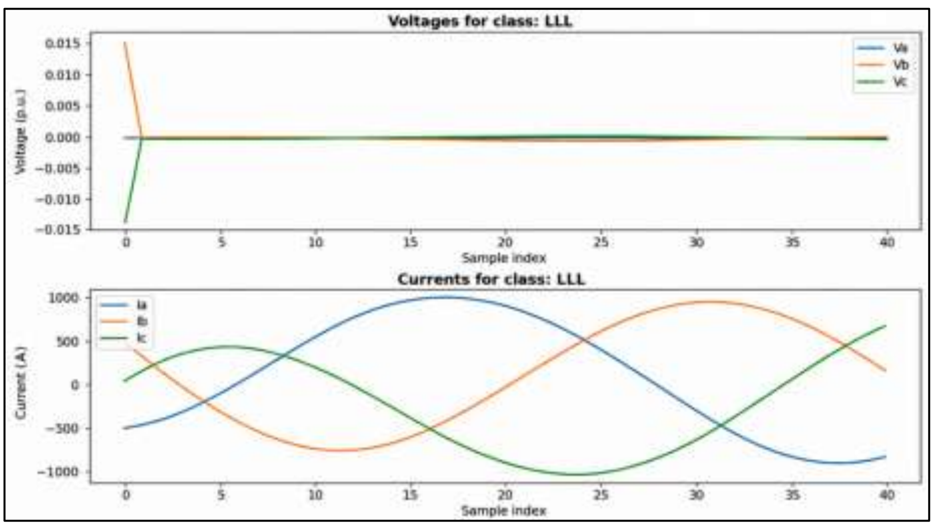

Figure 7. Voltage–current signal patterns under three-phase (LLL) fault conditions

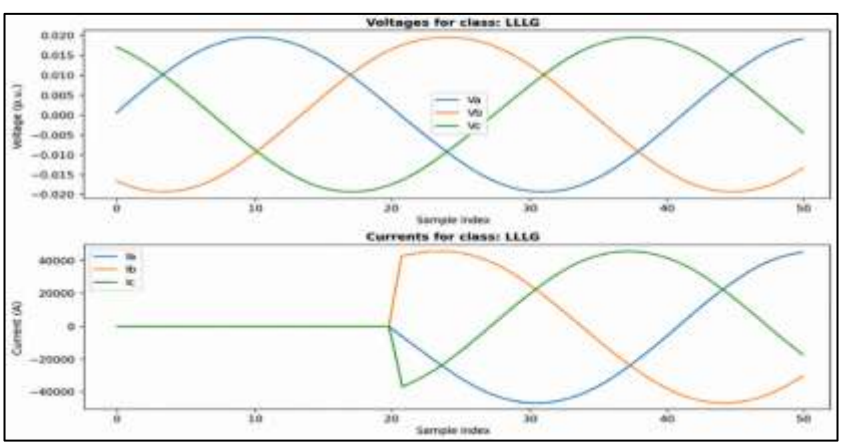

Figure 8. Voltage–current signal patterns during a three-phase-to-ground fault

2.3. Data Collection, Preparation and ML model analysis

Fault data is generated by simulating various fault scenarios in an IEEE 5-bus system using MATLAB/Simulink. Faults are applied at different locations and time instants to ensure dataset diversity. Data preprocessing steps include:

- Noise filtering
- Normalization
- Feature extraction
- Dataset labeling

The accuracy of classification is enhanced, and computational complexity is reduced by these procedures. In this study, the performance of various supervised machine learning models is analyzed using several classification algorithms [18] [19], including:

- Support Vector Machines (SVM)
- Decision Tree Classifiers
- Logistic Regression
- Random Forest Ensembles
- XGBoost Classifier

3. Results and Discussion

Logistic Regression shows limited performance in this study due to its linear decision boundary, which is insufficient to model complex fault patterns in power systems. However, it serves as a useful baseline model for understanding feature influence and comparing advanced machine learning techniques [20].

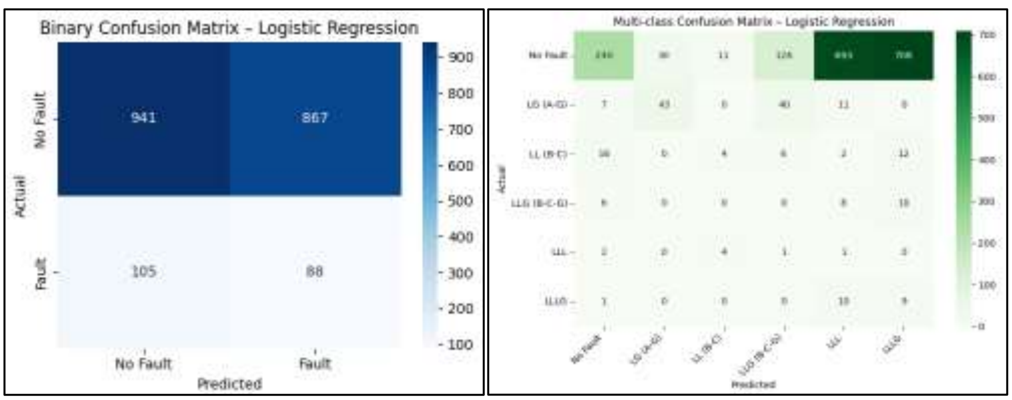

Figure 9. Logistic Regression confusion matrix: (a) binary case, (b) multi-class case.

Fig. 9a shows classification confusion matrix for a two-class problem, which illustrates 941 correctly predicted fault cases and 105 correctly predicted non-fault cases, whereas 88 samples were incorrectly labeled as faults and 867 samples were misclassified as non-faults. and Fig.9b shows the confusion matrix of multi-class classification model. The Logistic Regression model achieved an accuracy of 51.4%, indicating inadequate learning of complex nonlinear fault patterns in the IEEE 5-bus system. Also, Logistic Regression uses linear decision boundaries, which are insufficient to separate multiple fault classes that exhibit highly overlapping and nonlinear characteristics.

Fig. 10(a) illustrates evaluation of the binary classifier using a confusion matrix, where the Decision Tree correctly identifies 1768 fault cases and 44 non-fault cases, demonstrating strong detection capability. However, 149 instances are incorrectly flagged as faults, while 40 fault events are missed, indicating some misclassification. In general, the model's robust ability to differentiate between fault and no-fault conditions is substantiated by the substantial number of samples that were correctly classified.

Fig. 10(b) illustrates evaluation of the multi classifier using a confusion matrix, where the Decision Tree attempts to classify different fault types. Although the model maintains good predictive performance, a slight reduction in accuracy is observed compared to the binary case. This performance drop is mainly attributed to the increased complexity of distinguishing among multiple fault categories, overlapping feature characteristics, and similar electrical signatures of certain faults. Nevertheless, the results indicate that the Decision Tree model effectively handles both two class and multi-class fault classification tasks, with particularly strong performance in binary fault identification.

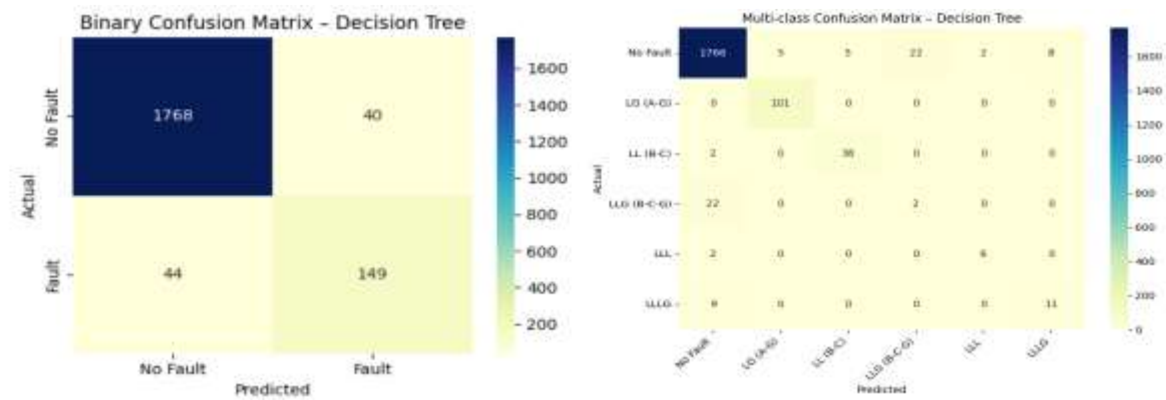

Figure 10. Decision Tree Confusion matrix: (a) Binary case, (b) Multi-class case

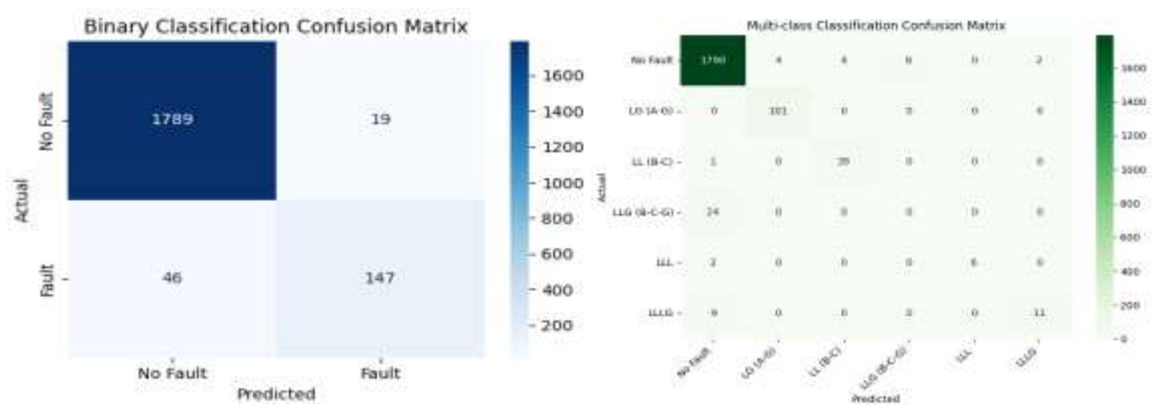

Figure 11. Random Forest Confusion matrix: (a) Binary case, (b) Multi-class case

Fig. 11a is a confusion matrix that shows model performance with 1789 fault instances and 46 normal cases, while producing 147 false alarms and 19 missed fault detections. and fig 11b shows the confusion matrix of multi-class classification model. The Random Forest classifier demonstrates superior performance in binary classification due to reduced class complexity, while a moderate drop in multiclass accuracy reflects the increased difficulty of distinguishing among multiple fault types. Nevertheless, the consistently high accuracy confirms the robustness and suitability of Random Forest for fault classification in power systems using both binary and multi-class approaches.

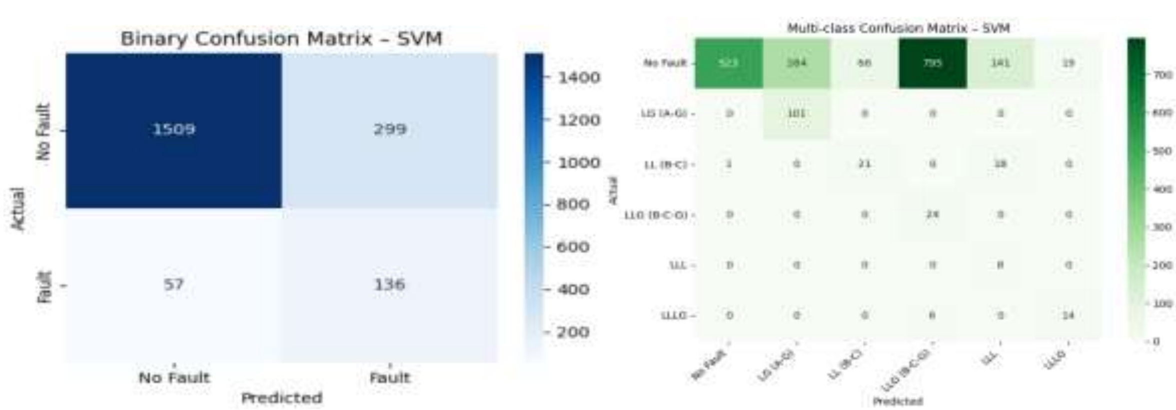

Figure 12. Support Vector Machine Confusion matrix: (a) Binary case, (b) Multi-class case

Fig. 12a is a confusion matrix that shows model performance with 1509 fault instances and 57 normal cases, while generating 136 false alarms and 299 missed fault detections and fig.12b shows the confusion matrix of multi-class classification model. The results show that binary classification achieves higher accuracy than multi-class classification. This is because binary classification involves distinguishing between only two classes, making the decision boundary simpler and reducing class overlap. In contrast, multi-class classification exhibits comparatively lower accuracy due to increased complexity, higher inter-class similarity, and greater chances of misclassification among multiple fault/condition categories.

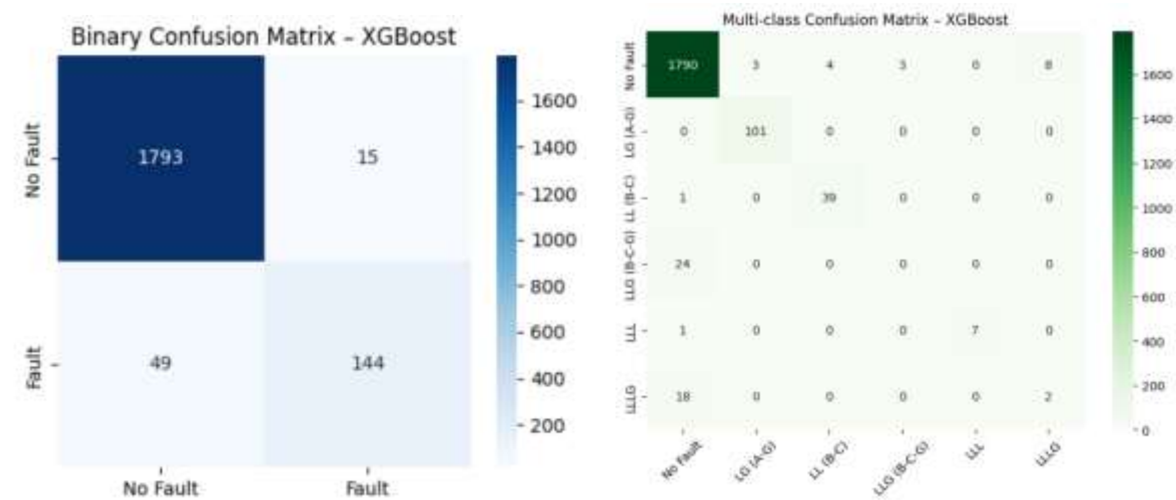

Figure.13. XGBoost Confusion matrix: (a) Binary case, (b) Multi-class case

Fig.13a is a confusion matrix that shows model performance with 1793 fault instances and 49 normal cases, while generating 144 false alarms and 15 missed fault detections and fig.13b shows the confusion matrix of multi-class classification model. The XGBoost model demonstrates higher accuracy in binary classification compared to multi-class classification. In the binary case, XGBoost effectively captures the discriminative patterns between the two classes, resulting in superior predictive performance. However, in the multi-class scenario, the accuracy shows a slight reduction due to the increased number of classes, overlapping feature distributions, and higher classification complexity.

The performance of the proposed models is analyzed using standard metrics—precision, recall, F1-score, and accuracy together with a detailed confusion matrix analysis. Logistic Regression shows limited performance for multi-class classification. Decision Tree performs well but may overfit. Random Forest attains the greatest levels of generalisation and accuracy. The computational effort required by SVM is higher, but it provides excellent accuracy.

The primary objective of this investigation is to utilise electrical measurement data to identify and classify defects in an IEEE 5-bus power system. Using three-phase voltage and current signals, the system differentiates between healthy operation and multiple fault conditions, including ground-related and inter-phase faults as well as three-phase disturbances. Different machine learning approaches are developed and validated for fault classification under both binary and multi-class conditions. The performance of the models is measured using widely adopted metrics, including accuracy, precision, recall, and F1-score, computed for each class. The comparative results of the different models are presented in Table 5.1, highlighting notable performance differences and demonstrating the effectiveness of ensemble-based approaches for accurate fault identification.

CLASS 0 : Binary Classification

CLASS 1 : Multi-class Classification

Table 1. Comparison of results for various ML models

Model	**Accuracy**	**F1-Score**	**F1-Score**	**Recall**	**Recall**	**Precision**	**Precision**
		CLAS 0	**CLAS 1**	**CLAS 0**	**CLAS 1**	**CLAS 0**	**CLAS 1**
Logistic Regression (LR)	0.1484	0.15	0.41	0.46	0.49	0.50	0.15

Support Vector Machine (SVM)	0.8220	0.66	0.31	0.77	0.75	0.64	0.34
XGBoost Classifier	0.9690	0.90	0.66	0.87	0.66	0.94	0.68
Random Forest	**0.9730**	**0.90**	**0.74**	**0.88**	**0.71**	**0.93**	**0.78**
Decision Tree	0.9615	0.88	0.71	0.87	0.72	0.88	0.70

Binary classification (Class 0) consistently outperforms multi-class classification (Class 1) across all models due to lower problem complexity. Logistic Regression shows the weakest performance, while SVM provides moderate results with noticeable degradation in multi-class classification. Among the evaluated models, XGBoost and Random Forest show superior performance; however, Random Forest outperforms the others by attaining the highest accuracy along with consistently balanced precision, recall, and F1-score values. Decision Tree performs reasonably well but remains inferior to ensemble-based approaches. Overall, Random Forest is the most effective model, followed closely by XGBoost. The results confirm that ensemble learning methods outperform individual classifiers for power system fault classification. Real-time protection applications are well-suited to Random Forest, which effectively captures non-linear relationships and exhibits robustness against noise and data variations.

Conclusion

This study applies machine learning techniques to identify and locate faults in an IEEE 5-bus power system under diverse operating conditions. A dataset generated using MATLAB/Simulink simulations, covering multiple fault types, is used to train and evaluate several classifiers, including Support Vector Machines, Logistic Regression, Decision Trees, Random Forest, and XGBoost. The results show that ensemble-based approaches outperform conventional models. Among them, Random Forest achieves the highest overall accuracy, along with well-balanced precision, recall, and F1-score, while XGBoost delivers comparable performance. It was also noted that binary classification (fault versus no-fault) produces superior results compared to multi-class classification, emphasising that the process of identifying the presence of a fault is less intricate than determining its specific category. The study confirms that machine learning approaches are highly appropriate for real-time monitoring and decision-support applications in modern power systems, as they can enhance the speed, accuracy, and reliability of fault diagnosis.

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