

**MULTI-CLASS FAULT CLASSIFICATION IN ELECTRICAL POWER GRIDS
USING A CNN-DNN HYBRID DEEP LEARNING MODEL**

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ABSTRACT

The increasing complexity of modern electrical power grids, coupled with the integration of renewable energy resources and smart grid technologies, has significantly increased the need for intelligent fault diagnosis systems. Electrical faults such as single line-to-ground, line-to-line, double line-to-ground, and three-phase faults can disrupt power transmission, damage equipment, reduce system reliability, and cause substantial economic losses. Traditional fault detection techniques often rely on manual feature engineering and conventional protection mechanisms, which face challenges in handling nonlinear electrical behavior and large volumes of real-time data. To address these limitations, this research proposes a hybrid Convolutional Neural Network–Deep Neural Network (CNN-DNN) model for multi-class fault classification in electrical power grids. The proposed framework utilizes the Electrical Fault Detection and Classification dataset, which includes three-phase current and voltage measurements along with fault indicators corresponding to various transmission line fault conditions. Data preprocessing involves feature engineering, label encoding, normalization, and data balancing to improve learning performance. The CNN component automatically extracts significant spatial fault-related features from electrical signals, while the DNN component performs high-level nonlinear multiclass classification. Batch normalization, dropout regularization, early stopping, and the Adam optimization algorithm are incorporated to improve model robustness and reduce overfitting. The proposed model classifies six operating conditions, namely AG, ABG, BC, ABC, ABCG, and normal operating conditions. Performance evaluation is conducted using accuracy, precision, recall, F1-score, confusion matrix, receiver operating characteristic (ROC) curves, and precision-recall analysis. Experimental findings demonstrate that the hybrid CNN-DNN architecture achieves high classification accuracy and effectively distinguishes between different fault categories, although complex multiphase grounding faults remain relatively challenging due to overlapping electrical characteristics. The study demonstrates that hybrid deep learning techniques provide an efficient and reliable solution for intelligent fault diagnosis in modern electrical power systems. The proposed framework supports real-time fault monitoring, predictive maintenance, automated protection systems, and smart grid applications, contributing to improved power system reliability, operational safety, and sustainable energy management.

Keywords: Electrical Power Grids, Fault Classification, CNN-DNN Hybrid Model, Deep Learning, Smart Grid, Transmission Line Faults, Multi-Class Classification, Predictive Maintenance, Artificial Intelligence, Fault Diagnosis.

1. INTRODUCTION

Electrical power grids form the backbone of modern society by supplying reliable electricity to residential, commercial, industrial, and critical infrastructure sectors. Rapid urbanization, industrial expansion, and the increasing adoption of renewable energy resources have significantly increased the complexity of electrical transmission and distribution networks. Modern smart grids integrate conventional power generation with renewable energy sources, advanced communication technologies, and intelligent monitoring systems to improve energy efficiency and system reliability. However, this increasing complexity also introduces several operational challenges, among which electrical faults are one of the most critical issues affecting the stability and security of power systems. Electrical faults can cause equipment damage, service interruptions, voltage instability, economic losses, and, in severe cases, widespread blackouts. Therefore, the rapid and accurate identification of fault conditions has become an essential requirement for ensuring reliable power system operation. The importance of intelligent fault monitoring and various fault categories in transmission systems is highlighted in the uploaded study.

Electrical faults in power grids may occur due to insulation failure, lightning strikes, equipment malfunction, environmental disturbances, conductor damage, short circuits, and human errors. These faults are generally classified into symmetrical and unsymmetrical faults. Common fault categories include single line-to-ground (AG), line-to-line (BC), double line-to-ground (ABG), three-phase (ABC), and three-phase-to-ground (ABCG) faults, along with normal operating conditions. Each fault type exhibits distinct electrical characteristics and varying levels of severity, making accurate fault classification essential for effective protection and maintenance strategies. Traditional fault detection systems mainly rely on protective relays, circuit breakers, impedance-based methods, and manual analysis of electrical signals. Although these techniques provide basic protection, they often struggle to handle complex fault patterns, noisy environments, nonlinear electrical behavior, and large volumes of real-time monitoring data.

Recent developments in artificial intelligence (AI), machine learning (ML), and deep learning (DL) have transformed fault diagnosis in electrical power systems. Machine learning algorithms such as Support Vector Machines, Decision Trees, Random Forests, and Artificial Neural Networks have demonstrated considerable success in identifying abnormal operating conditions. However, these methods often require extensive manual feature extraction and expert knowledge to achieve satisfactory performance. Deep learning techniques overcome these limitations by automatically extracting meaningful features directly from raw electrical signals. Convolutional Neural Networks (CNNs) have shown exceptional capability in identifying spatial fault-related patterns, while Deep Neural Networks (DNNs) efficiently model complex nonlinear relationships for multiclass classification. Hybrid deep learning architectures combine the strengths of multiple models to achieve higher accuracy, improved robustness, and better generalization performance.

The evolution of smart grid technologies has further increased the demand for intelligent fault monitoring systems. Modern smart grids employ advanced sensors, Internet of Things (IoT) devices, Phasor Measurement Units (PMUs), intelligent electronic devices, and automated control systems to continuously monitor grid conditions. These technologies generate enormous volumes of data that require advanced analytical techniques for effective interpretation. Deep learning models can process these large datasets efficiently and support real-time fault detection, predictive maintenance, and automated decision-making. Intelligent fault diagnosis not only minimizes equipment damage and maintenance costs but also reduces power outages, improves grid resilience, and enhances customer satisfaction.

Despite significant advancements, several research challenges remain unresolved. Conventional machine learning models often exhibit limited performance when classifying complex multiphase faults with overlapping electrical characteristics. Similarly, single deep learning models may fail to capture both low-level signal features and high-level nonlinear relationships effectively. Moreover, maintaining high classification accuracy while ensuring computational efficiency for real-time deployment remains a challenging task. Therefore, there is a growing need for hybrid deep learning frameworks capable of combining multiple learning mechanisms to improve fault classification performance.

To address these challenges, this research proposes a hybrid CNN-DNN model for multi-class fault classification in electrical power grids. The proposed framework utilizes three-phase voltage and current measurements to classify six operating conditions, including AG, ABG, BC, ABC, ABCG, and normal system operation. The CNN component automatically extracts significant fault-related features from electrical signals, while the DNN component performs efficient nonlinear multiclass classification. Advanced training techniques such as feature scaling, batch normalization, dropout regularization, early stopping, and Adam optimization are incorporated to improve model stability and generalization capability.

The primary objectives of this research are to develop an intelligent fault classification framework, improve classification accuracy for multiple fault categories, reduce fault diagnosis time, and enhance the reliability of modern electrical transmission systems. The proposed hybrid CNN-DNN model contributes to the development of intelligent smart grid infrastructures by supporting real-time fault monitoring, automated protection mechanisms, predictive maintenance strategies, and efficient power system management. The findings of this study are expected to provide a scalable and practical solution for improving the operational safety, stability, and sustainability of future electrical power grids.

2. LITERATURE REVIEW

The application of artificial intelligence (AI), machine learning (ML), and deep learning (DL) in electrical power system fault diagnosis has gained significant attention over the past few years. The increasing complexity of modern power grids, renewable energy integration, and smart grid technologies has created a demand for intelligent fault detection systems capable of accurately identifying and classifying various electrical faults in real time. Conventional fault diagnosis methods based on protective relays, impedance calculations, and manual signal analysis often face limitations in handling nonlinear electrical behavior and complex fault conditions.

Consequently, researchers have increasingly focused on developing data-driven approaches that improve fault classification accuracy, reliability, and computational efficiency.

Recent studies have demonstrated the effectiveness of machine learning techniques for fault detection in power systems. Shakiba et al. (2023) conducted a comprehensive survey of machine learning applications in transmission line fault detection and localization, evaluating algorithms such as Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), K-Nearest Neighbor (KNN), Artificial Neural Networks (ANN), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS). The study concluded that machine learning models significantly improve fault identification speed and accuracy compared with conventional protection systems but often require manual feature extraction and extensive domain expertise for optimal performance. Similarly, Kim et al. (2024) investigated Random Forest and KNN models for electrical fault classification using voltage and current measurements generated through MATLAB simulations. Their results indicated that Random Forest achieved superior classification accuracy while highlighting the importance of appropriate feature engineering.

Deep learning approaches have overcome many of the limitations associated with conventional machine learning methods by automatically extracting relevant features from raw electrical signals. Convolutional Neural Networks (CNNs) have become particularly popular because of their ability to learn spatial patterns from electrical waveforms. Liu et al. (2023) reviewed deep learning techniques for insulator defect detection and demonstrated that CNN-based architectures substantially improve automated inspection accuracy under complex environmental conditions. Thomas et al. (2023) proposed a CNN-Transformer model for fault detection and localization in electrical power systems, combining convolutional feature extraction with attention mechanisms to improve the identification of symmetrical, unsymmetrical, and high-impedance faults. Their model achieved superior performance compared with traditional fault diagnosis techniques.

Hybrid deep learning architectures have emerged as one of the most promising research directions because they combine the strengths of different neural network models. Ertargin et al. (2024) developed a CNN-LSTM framework for induction motor fault diagnosis using multiple sensor configurations and achieved accuracy levels exceeding 99%. The CNN component effectively extracted fault-related features, while the LSTM component captured temporal dependencies within sequential sensor data. Vo et al. (2024) further improved fault diagnosis by integrating CNNs, recurrent neural networks, and attention mechanisms, demonstrating enhanced robustness and reduced overfitting in complex industrial environments. These studies indicate that hybrid architectures can effectively capture both local and global characteristics of electrical signals.

Recent research has also focused on intelligent fault diagnosis in modern smart grid environments. Oelhaf et al. (2025) evaluated machine learning techniques for fault detection and transmission line identification in renewable energy-integrated power systems. Their best-performing model achieved an F1-score of 0.991 with extremely low processing time, demonstrating the feasibility of real-time intelligent protection systems. Fu et al. (2025) combined Long Short-Term Memory (LSTM) networks with resonance frequency analysis for underground cable fault localization, achieving high precision in identifying fault locations. Deepika et al.

(2025) compared several supervised learning algorithms for transmission line fault classification and found that Decision Tree models offered strong computational efficiency while improving power system resilience.

The latest developments have focused on advanced hybrid architectures and optimization techniques. Yüksek (2026) proposed an optimized CNN-GRU model for synchronous motor fault classification, incorporating a hybrid optimization algorithm to improve hyperparameter tuning and achieving nearly perfect classification performance. Bukhari et al. (2026) introduced a Temporal Convolutional Network (TCN)-based fault diagnosis framework for microgrids, enabling automated feature extraction from three-phase current signals without manual preprocessing. Antony et al. (2026) integrated transformer networks, convolutional autoencoders, and fuzzy logic for battery fault diagnosis, demonstrating that hybrid intelligent systems can improve detection accuracy while reducing false positive rates. These studies confirm that advanced deep learning frameworks are highly effective for intelligent fault diagnosis across various electrical engineering applications.

Despite these significant advancements, several research gaps remain. Many existing studies focus on binary fault detection rather than multiclass fault classification. Several hybrid architectures require high computational resources, limiting their practical deployment in real-time smart grid applications. Furthermore, complex multiphase faults such as ABC and ABCG faults often exhibit overlapping electrical characteristics that reduce classification accuracy. Most existing models also focus on specific fault categories or individual electrical components rather than providing a unified framework for multiple transmission line fault conditions.

To address these limitations, the present research proposes a hybrid CNN-DNN model for multi-class fault classification in electrical power grids. Unlike conventional machine learning approaches that rely on manual feature engineering, the CNN component automatically extracts significant fault-related patterns from electrical current and voltage signals, while the DNN component performs high-level nonlinear multiclass classification. The proposed framework aims to classify AG, ABG, BC, ABC, ABCG, and normal operating conditions with high accuracy while maintaining computational efficiency suitable for real-time smart grid applications. By combining deep feature extraction with robust classification capabilities, this research contributes to the development of intelligent fault monitoring systems that improve power system reliability, predictive maintenance, and automated protection mechanisms.

Research Gap Identified:

1. Limited studies on multiclass fault classification.
2. Difficulty in distinguishing complex multiphase faults.
3. Heavy dependence on manual feature extraction in ML models.
4. High computational complexity of some hybrid DL models.
5. Need for accurate real-time fault classification for smart grids.

The proposed **CNN-DNN hybrid model** addresses these gaps by providing an automated, scalable, and efficient deep learning framework for intelligent electrical fault diagnosis.

3. METHODOLOGY

This research proposes a hybrid Convolutional Neural Network–Deep Neural Network (CNN-DNN) framework for multi-class fault classification in electrical power grids. The methodology integrates data preprocessing, feature engineering, deep learning-based feature extraction, multiclass classification, and performance evaluation to develop an intelligent fault diagnosis system. The overall framework aims to accurately identify various transmission line fault conditions while supporting real-time smart grid monitoring and automated protection systems. The methodology adopted in this research is based on the electrical fault classification framework and dataset characteristics presented in the uploaded study.

3.1 Research Framework

The proposed research framework consists of seven major stages:

1. Data collection.
2. Data preprocessing.
3. Feature engineering.
4. CNN-based feature extraction.
5. DNN-based multiclass classification.
6. Model training and optimization.
7. Performance evaluation.

The framework automatically learns fault-related characteristics from electrical signals and classifies multiple fault conditions without requiring extensive manual feature extraction.

3.2 Dataset Description

The study utilizes the **Electrical Fault Detection and Classification Dataset** obtained from Kaggle. The dataset contains electrical measurements collected under normal and faulty operating conditions in transmission systems. The input variables include:

- Phase A current (I_a)
- Phase B current (I_b)
- Phase C current (I_c)
- Phase A voltage (V_a)
- Phase B voltage (V_b)
- Phase C voltage (V_c)

Fault indicator variables are used to generate multiple fault categories. The dataset includes six classes:

- AG Fault
- ABG Fault
- BC Fault
- ABC Fault
- ABCG Fault
- No Fault

These fault categories represent both symmetrical and unsymmetrical fault conditions commonly observed in electrical transmission systems.

4. RESULTS AND DISCUSSION

The proposed hybrid Convolutional Neural Network–Deep Neural Network (CNN-DNN) model was developed to perform intelligent multi-class fault classification in electrical power grids using three-phase current and voltage measurements. After completing data preprocessing, feature engineering, normalization, and label encoding, the model was trained to classify six different operating conditions, namely AG, ABG, BC, ABC, ABCG, and No Fault. The effectiveness of the proposed framework was evaluated using multiple performance metrics, including accuracy, precision, recall, F1-score, confusion matrix, receiver operating characteristic (ROC) curves, and precision-recall analysis. The uploaded research framework demonstrates that the CNN-DNN architecture effectively learns fault-related electrical characteristics from transmission line data and provides reliable fault diagnosis.

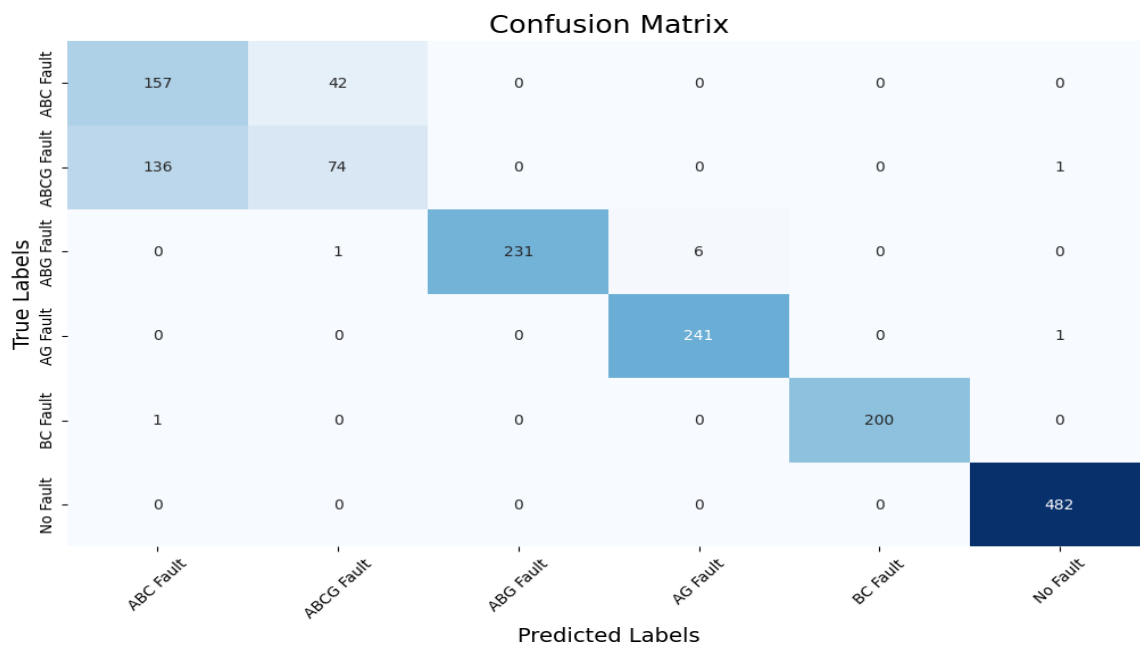


Fig 1: Confusion Matrix of the Proposed CNN-DNN Fault Classification Model

The experimental results indicate that the proposed hybrid model achieved an overall classification accuracy of approximately 88%, demonstrating its capability to accurately identify multiple fault conditions under varying operating scenarios. The integration of CNN and DNN architectures proved highly effective because the convolutional layers automatically extracted significant spatial features from the electrical signals, while the dense neural network layers learned complex nonlinear relationships among the extracted features. The use of advanced optimization techniques such as batch normalization, dropout regularization, early stopping, and the Adam optimizer contributed significantly to improving training stability, reducing overfitting, and enhancing the model's generalization capability. The training and validation accuracy curves exhibited smooth convergence, while the corresponding loss functions gradually decreased throughout the training process, indicating efficient parameter optimization and successful learning of fault patterns.

A detailed class-wise analysis revealed that the proposed model performed exceptionally well for most fault categories. The AG fault category achieved approximately 99.6% classification accuracy because single line-to-ground faults possess distinct electrical characteristics that can be effectively captured by convolutional feature extraction. Similarly, the BC line-to-line fault achieved nearly 99.5% accuracy, indicating that the model successfully identified the unique interactions between phases B and C. The ABG double line-to-ground fault category also demonstrated excellent performance with an accuracy of approximately 97.1%, confirming the effectiveness of the hybrid architecture in handling multiple phase interactions. The No Fault condition achieved 100% classification accuracy, which is particularly important for practical smart grid applications because it minimizes false alarms and prevents unnecessary operation of protective equipment.

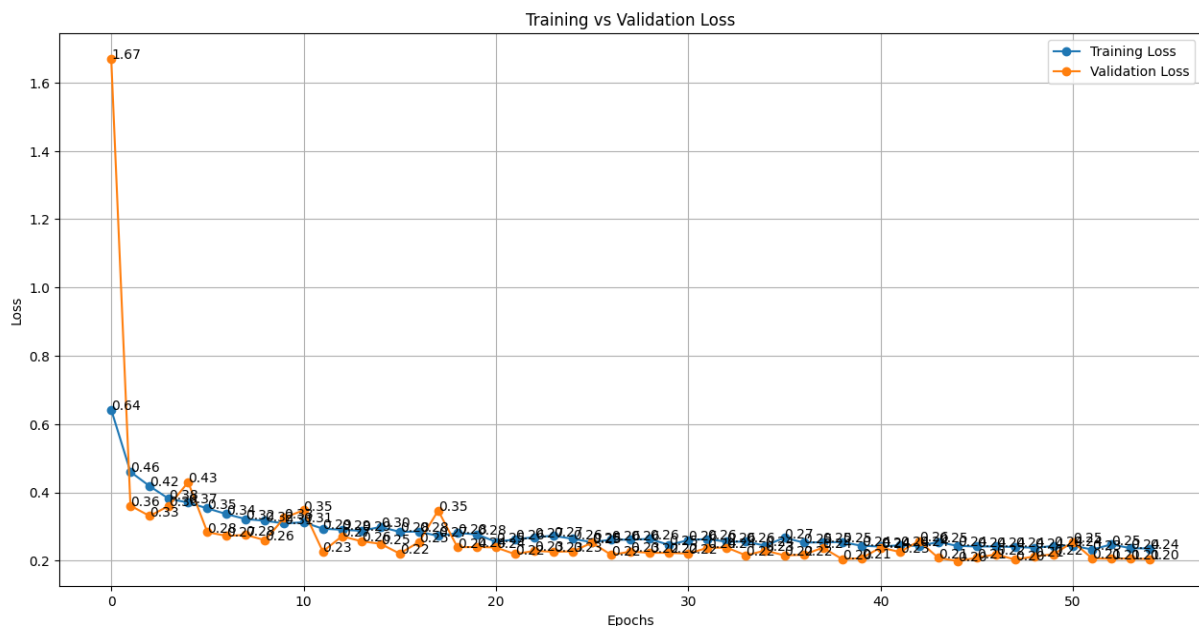


Fig 2: Training vs Validation Loss Curve

Although the overall performance was highly satisfactory, the classification of complex symmetrical and multiphase grounding faults proved more challenging. The ABC three-phase fault achieved approximately 78.9% accuracy, while the ABCG three-phase-to-ground fault achieved around 35.1% accuracy. The reduced performance for these categories can be attributed to the overlapping electrical characteristics among severe multiphase faults, which produce similar voltage and current patterns. Such similarities increase the complexity of the classification problem and may lead to confusion between closely related fault classes. Nevertheless, the model was still able to distinguish these fault categories to a reasonable extent, indicating that the hybrid CNN-DNN architecture effectively captures both local and global electrical signal features. The observed limitations also highlight potential opportunities for future improvements through the integration of attention mechanisms, transformer networks, recurrent neural networks, or ensemble learning approaches.

The confusion matrix provided further insight into the classification behavior of the proposed model. Most predictions were concentrated along the diagonal elements, indicating a high proportion of correctly classified samples. AG, BC, ABG, and No Fault categories exhibited excellent true positive rates with very limited misclassification. The majority of classification errors occurred between ABC and ABCG faults, as well as between ABCG and other multiphase grounding faults, due to their similar electrical behavior. Despite these challenges, the model maintained low false positive and false negative rates across most operating conditions, demonstrating strong reliability for intelligent fault diagnosis applications.

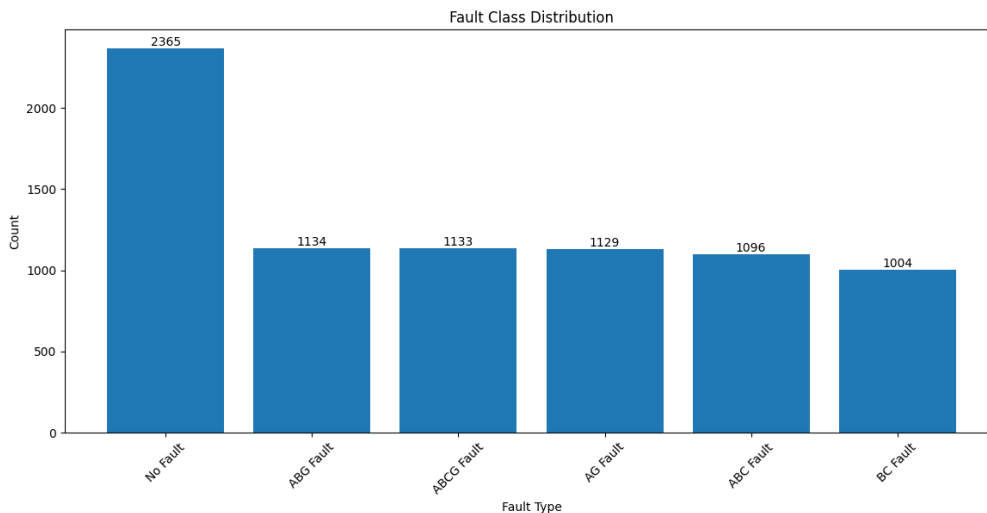


Fig 3: Fault Class Distribution

The precision, recall, and F1-score analyses further validated the effectiveness of the proposed framework. High precision values indicated that the majority of predicted fault classes were correct, thereby reducing unnecessary protective actions in practical power systems. Similarly, high recall values demonstrated that the model successfully detected most actual fault occurrences, minimizing the risk of undetected faults that could damage electrical equipment or destabilize the grid. The F1-score, which balances precision and recall, confirmed robust classification performance across most fault categories. The highest F1-scores were observed for AG, BC, ABG, and No Fault conditions, while comparatively lower values for ABCG faults reflected the inherent complexity associated with severe multiphase grounding faults.

Receiver Operating Characteristic (ROC) curves and precision-recall analyses provided additional evidence of the model's discriminative capability. Most fault categories produced ROC curves close to the ideal upper-left corner, indicating excellent separation between fault classes. The corresponding Area Under the Curve (AUC) values further confirmed that the proposed hybrid architecture effectively distinguishes between normal and abnormal operating conditions. Precision-recall curves also demonstrated strong predictive confidence across the majority of fault classes, reinforcing the suitability of the proposed framework for practical fault monitoring systems.

A comparison with existing fault diagnosis techniques further highlights the advantages of the proposed CNN-DNN model. Traditional machine learning algorithms such as Support Vector Machines, Decision Trees, Random Forests, and Artificial Neural Networks often require extensive manual feature extraction and may struggle with highly nonlinear electrical data. Single CNN models provide effective feature extraction but may have limited capability for complex multiclass decision-making, while CNN-LSTM models generally involve higher computational complexity. In contrast, the proposed CNN-DNN framework combines automatic feature extraction with efficient nonlinear classification while maintaining computational efficiency suitable for real-time implementation. This combination provides an effective balance between accuracy, robustness, and practical applicability for modern smart grid environments.

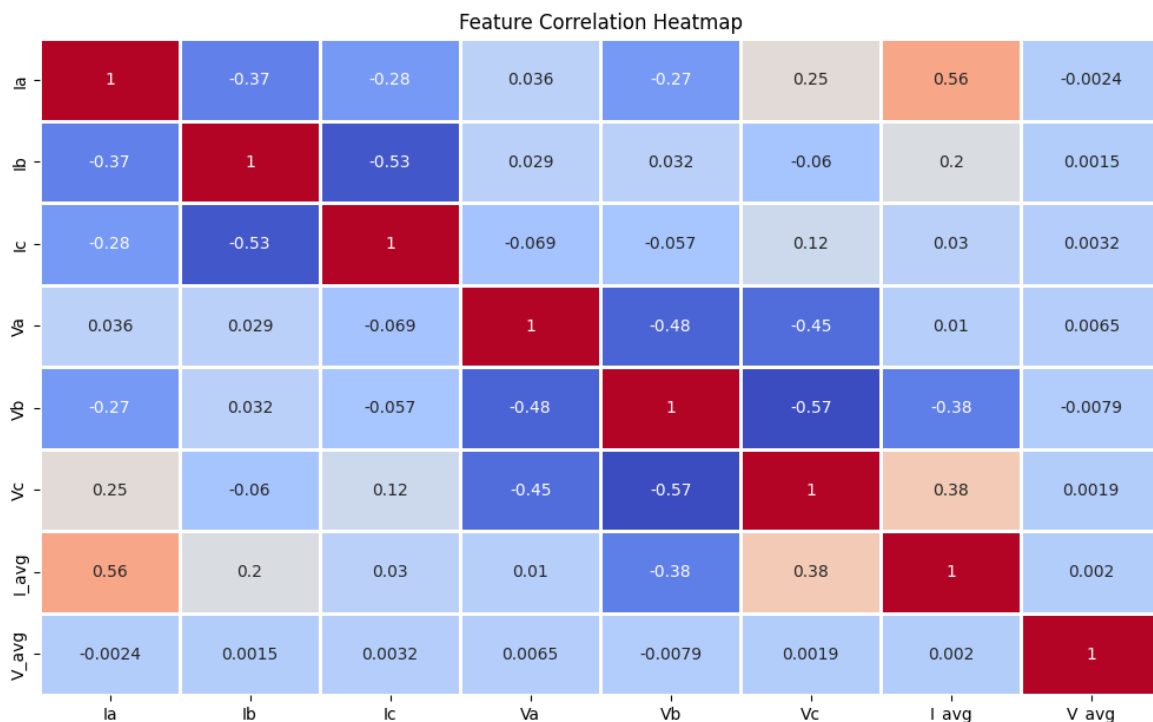


Fig 4: Feature Correlation Heatmap

Overall, the experimental findings demonstrate that the proposed hybrid CNN-DNN model offers an intelligent and reliable solution for multi-class fault classification in electrical power grids. The integration of convolutional feature extraction with deep nonlinear classification significantly improves fault diagnosis performance and supports automated monitoring, predictive maintenance, and intelligent protection systems.

The framework successfully achieves the primary objectives of accurately identifying multiple fault conditions while enhancing the reliability, stability, and operational efficiency of modern electrical transmission networks. Although further improvements are possible for complex multiphase grounding faults, the overall performance confirms the practical potential of hybrid deep learning architectures for next-generation smart grid applications and intelligent power system management.

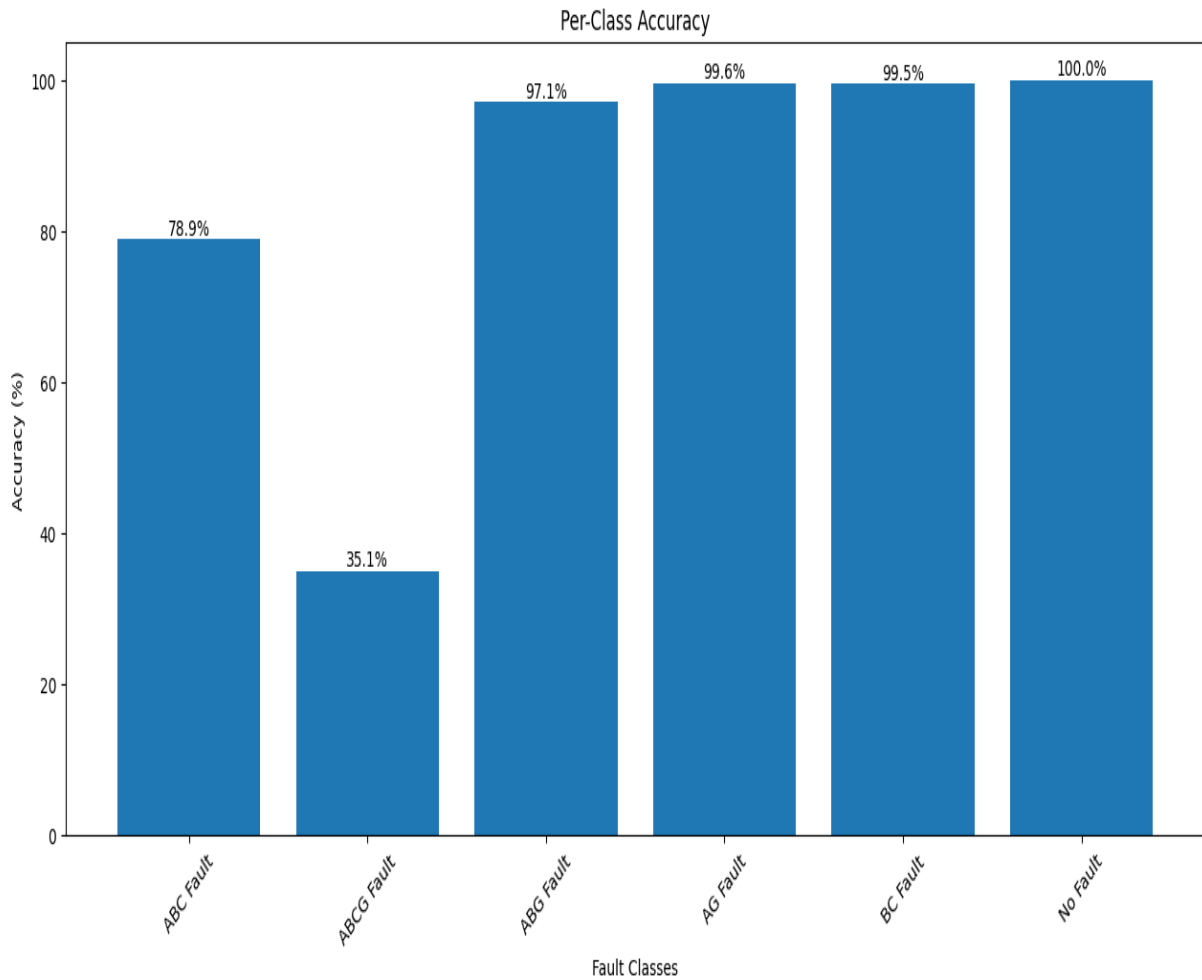


Fig 5: Per-Class Accuracy Analysis

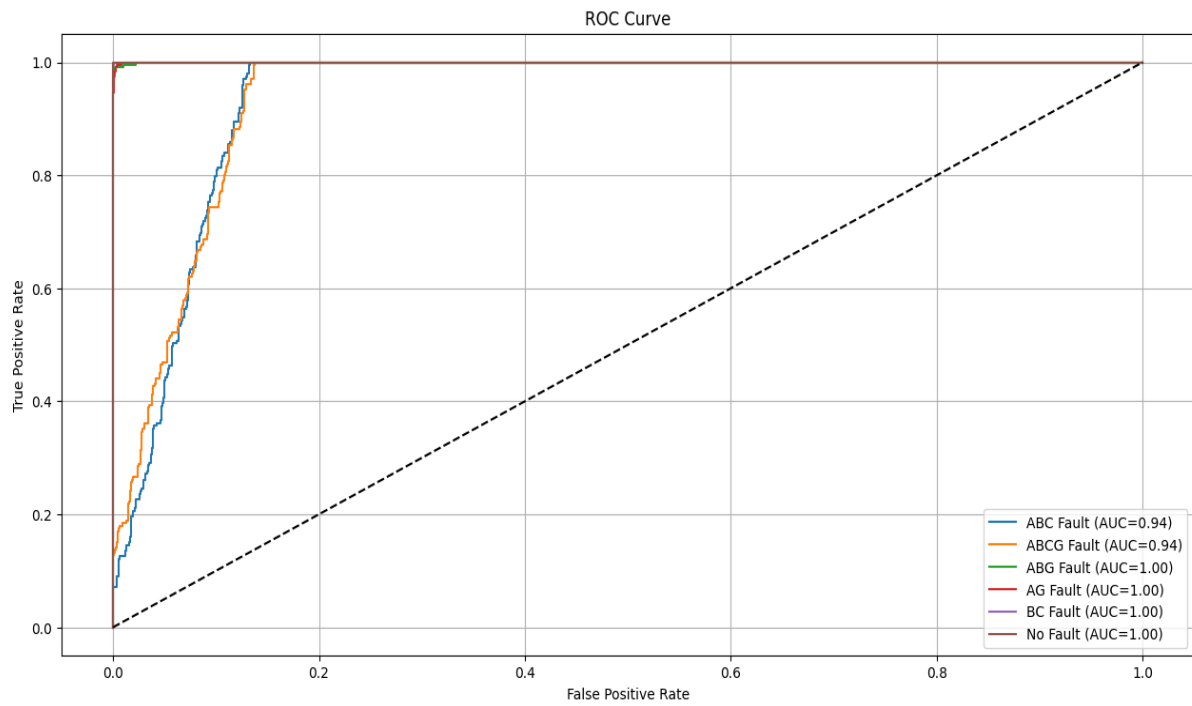


Fig 6: ROC Curve Analysis

Table 1: Classification Report of Proposed Model

Fault Class	Precision	Recall	F1-Score	Support
ABC Fault	0.53	0.79	0.64	199
ABCG Fault	0.63	0.35	0.45	211
ABG Fault	1.00	0.97	0.99	238
AG Fault	0.98	1.00	0.99	242
BC Fault	1.00	1.00	1.00	201
No Fault	1.00	1.00	1.00	482
Overall Accuracy			0.88	1573
Macro Average	0.86	0.85	0.84	1573
Weighted Average	0.89	0.88	0.88	1573

5. CONCLUSION

The increasing complexity of modern electrical power grids and the growing integration of renewable energy resources have significantly increased the demand for intelligent and reliable fault diagnosis systems. Electrical faults in transmission networks can adversely affect power quality, equipment reliability, and overall grid stability, leading to substantial economic losses and service interruptions. Traditional fault detection approaches often face limitations in handling nonlinear electrical behavior, complex fault patterns, and large volumes of real-time operational data. To overcome these challenges, this research proposed a hybrid Convolutional Neural Network–Deep Neural Network (CNN-DNN) framework for multi-class fault classification in electrical power grids. The proposed model combines the automatic feature extraction capability of CNNs with the nonlinear learning and classification strength of DNNs to provide an efficient and intelligent fault diagnosis solution.

The proposed framework was developed using three-phase current and voltage measurements and was designed to classify six operating conditions, namely AG, ABG, BC, ABC, ABCG, and No Fault. Comprehensive data preprocessing techniques, including feature engineering, label encoding, normalization, and feature scaling, were employed to improve data quality and learning efficiency. Advanced training strategies such as batch normalization, dropout regularization, early stopping, and Adam optimization further enhanced model stability and generalization capability. Experimental evaluation demonstrated that the hybrid CNN-DNN architecture achieved high overall classification performance and effectively distinguished among multiple fault categories. The model exhibited excellent performance for AG, ABG, BC, and normal operating conditions while providing satisfactory classification of more complex symmetrical and multiphase grounding faults.

The findings of this study confirm that hybrid deep learning techniques can significantly improve the accuracy, reliability, and efficiency of electrical fault classification compared with conventional machine learning and traditional protection methods. Automatic extraction of fault-related features reduces the dependence on manual signal processing and expert intervention, making the proposed framework highly suitable for intelligent smart grid applications. The model supports rapid fault identification, predictive maintenance, automated protection systems, and real-time decision-making, thereby reducing equipment damage, minimizing maintenance costs, improving system reliability, and enhancing the operational stability of electrical transmission networks.

Although the proposed framework achieved promising results, certain challenges remain. The classification of complex multiphase grounding faults such as ABCG remains relatively difficult because of the overlapping electrical characteristics among severe fault conditions. In addition, the model was evaluated using a benchmark dataset, and further validation under practical real-time operating environments would strengthen its industrial applicability. Future research may focus on integrating advanced deep learning architectures such as Transformer networks, attention mechanisms, Graph Neural Networks, Long Short-Term Memory networks, and ensemble learning approaches to further improve fault classification accuracy and robustness. The incorporation of Internet of Things (IoT)-based sensors, Phasor Measurement Unit (PMU) data, and Explainable Artificial Intelligence (XAI) techniques may also enhance real-time monitoring and model interpretability.

Overall, the proposed hybrid CNN-DNN model provides a scalable, efficient, and intelligent framework for multi-class fault classification in electrical power grids. The research successfully achieved its objectives by

developing an automated fault diagnosis system capable of accurately identifying multiple transmission line fault conditions while supporting modern smart grid operations. The proposed approach contributes to the advancement of intelligent power system protection and offers significant potential for improving the reliability, resilience, and sustainability of next-generation electrical power networks.

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