Proposing A Fine-Tuned Deep Learning Framework for Accurate Fault Detection and Classification in Smart Grid Transmission Line

Shahinur Rahman [1,*]

1 Department of Electrical and Electronic Engineering , Faculty of Science and Technology, City University, Bangladesh, Khagan, Savar, Dhaka, Bangladesh

* Corresponding author,e-mail: shahinurislamkowser@gmail.com

Abstract—Accurate fault diagnosis plays a crucial role in ensuring the stability and reliability of smart grid transmission systems. In this study, a state-of-the-art deep learning approach is developed and fine-tuned for both binary fault detection and multi-class fault classification tasks. Using current and voltage datasets, a robust preprocessing pipeline is implemented, including standardization and label encoding for six distinct fault categories. Two tailored deep learning architectures are designed using sequential models with dense and dropout layers to effectively capture the nonlinear characteristics of grid data. Experimental results demonstrate the effectiveness of the proposed framework in anomaly detection, where the fault detection model achieves 100% test accuracy with an almost ideal AUC of 0.9999. The fault classification model achieves an overall accuracy of 86%, showing strong performance across most classes, particularly for single line-to-ground faults. However, detailed analysis using confusion matrices reveals challenges in correctly identifying more complex fault combinations, such as “LLL fault (three-phase fault)” and “LLLG fault (three-phase symmetrical fault).” Supported by comprehensive evaluation metrics and visualizations, the proposed framework demonstrates strong potential for real-time grid monitoring while also highlighting key areas for improvement in handling minority and complex fault classes.

Keywords—Deep Learning, Fault Classification, Fault Detection, Neural Networks, Smart Grid, Transmission Lines

I. INTRODUCTION

The rapid evolution of modern smart grids has significantly improved the efficiency, automation, and reliability of electrical power systems. Smart grid transmission networks integrate advanced sensing, communication, and control technologies to ensure stable electricity delivery and real-time system monitoring. However, transmission lines remain highly vulnerable to different types of faults caused by lightning strikes, insulation breakdown, environmental disturbances, equipment aging, and short-circuit conditions. These faults may result in severe power outages, equipment damage, and economic losses if they are not detected and classified promptly. Therefore, accurate fault detection and classification are essential for maintaining the reliability and stability of smart grid transmission systems [1].

Conventional fault diagnosis techniques, including impedance-based relays, Fourier transform, and wavelet transform methods, have been widely applied in power system protection. Although these techniques provide acceptable performance in controlled environments, they often suffer from limited adaptability under noisy and dynamic operating conditions. In addition, traditional methods usually depend on handcrafted feature extraction and expert-defined thresholds, making them less effective for handling large-scale smart grid data and complex fault scenarios [2].

Recently, artificial intelligence (AI) and deep learning (DL) techniques have emerged as powerful solutions for intelligent fault analysis in smart grids. Deep learning models can automatically extract meaningful features from voltage and current signals and effectively learn nonlinear relationships in transmission line data. Various architectures such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and hybrid deep learning frameworks have demonstrated promising performance for fault detection and classification tasks [3]. Moreover, recent studies have shown that deep learning-based systems can achieve high detection accuracy even under noisy conditions and varying grid operating environments [4].

Despite significant progress, several challenges remain unresolved in transmission line fault diagnosis. Many existing studies mainly focus on either binary fault detection or fault localization, while reliable multi-class fault classification remains difficult, particularly for complex faults such as three-phase symmetrical faults and combined fault conditions. Additionally, class imbalance, overlapping signal characteristics, and limited generalization capability continue to reduce classification performance in practical applications [5]. Therefore, there is still a strong need for robust and fine-tuned deep learning frameworks capable of achieving both accurate fault detection and efficient fault classification in real-time smart grid systems.

Motivated by these challenges, this paper proposes a fine-tuned deep learning framework for accurate fault detection and classification in smart grid transmission lines. The proposed approach utilizes both current and voltage datasets and applies an effective preprocessing pipeline involving standardization and label encoding for six different fault categories. Two customized sequential deep learning architectures using dense and dropout layers are developed to effectively capture complex nonlinear characteristics of transmission line signals. The proposed framework performs both binary fault detection and multi-class fault classification with high effectiveness. Experimental results demonstrate excellent fault detection capability with 100% testing accuracy and near-perfect AUC performance, while the classification model achieves strong overall accuracy across multiple fault categories. Furthermore, confusion matrix analysis and detailed evaluation metrics provide valuable insights into the model’s strengths and limitations, especially for complex fault combinations. The proposed framework can support intelligent real-time monitoring and improve the reliability of modern smart grid protection systems.

II. LITERATURE REVIEW

Fault detection and classification in transmission lines remain central to the reliability and stability of smart grid systems. Recent research shows a clear shift from conventional signal-processing methods toward machine learning, deep learning, and explainable AI frameworks. These approaches are increasingly used to improve detection accuracy, reduce misclassification, and support real-time decision-making in complex grid environments.

Ali and Esmail [1] proposed a deep learning framework combined with wavelet packet transform for fault diagnosis in double-circuit transmission lines. Their work demonstrated strong fault section identification and fault location performance using three-phase current and voltage signals. A major strength of this study is its hybrid use of signal decomposition and deep learning, which improved robustness across different fault scenarios. However, the method still depends on simulation-based data, and the authors noted the need for real-time acquisition systems, adaptive learning, and improved preprocessing to support deployment in practical environments.

Hossain et al. [3] introduced an adaptive fault diagnosis method based on an LSTM autoencoder. Unlike supervised classification methods, their model learned normal operating patterns and detected faults as anomalies. This unsupervised strategy is valuable for modern grids because it can handle unseen or evolving faults. The study reported high accuracy, low false positive rates, and strong noise resilience. Still, the authors acknowledged that generalization across diverse grid topologies and integration with legacy protection systems require further investigation.

Tilak Giri et al. [4] proposed an explainable CNN-Transformer model for transmission line fault detection and classification. Their work is important because it combines high predictive performance with explainability through SHAP analysis. The model outperformed several strong baselines, including XGBoost, LSTM, LSTM-GRU, ViT, and ELM. This supports the idea that hybrid deep learning architectures can capture both local patterns and long-range dependencies in grid signals. At the same time, the authors highlighted limitations related to deployment under electromagnetic noise, fluctuating loads, and field validation across different grid configurations.

Uzel et al. [6] developed an optimized ANN-RF hybrid model with Optuna for transmission fault detection and classification. Their framework used synthetic MATLAB/Simulink data, SMOTE for class balancing, and hyperparameter optimization to achieve very high accuracy. This study is notable because it shows how ensemble learning and optimization can improve performance on imbalanced fault data. However, the reliance on simulated data and the computational cost of the model suggest the need for lightweight and real-world validated systems before practical deployment.

Anwar et al. [7] investigated ensemble machine learning models for fault detection and classification in transmission lines. Their findings confirm that ensemble-based systems can deliver strong diagnostic performance and improve grid reliability. However, they also noted that such models often require large datasets and longer training times, which can limit real-time use in resource-constrained systems. This study therefore reinforces the trade-off between accuracy and computational efficiency in practical fault diagnosis.

Zhang et al. [8] presented HSPAN-GNN, a graph-neural-network-based approach for visual fault detection in transmission lines. Their method addressed low-resolution and small-target detection problems through graph convolution, SPD-Conv, and attention normalization. Although the study is more focused on transmission line detection than fault classification, it is relevant because it demonstrates the growing role of lightweight and efficient neural architectures in power-system monitoring. The authors, however, acknowledged that the model still requires streamlining to reduce computational overhead for mobile or low-power platforms.

In systems with renewable integration, Sonora Dixit et al. [9] studied fault classification in wind distributed generation integrated transmission lines using ANN. Their work showed that neural-network-based classification can successfully identify fault types under distributed generation penetration. This is especially important for modern smart grids, where renewable sources alter fault behavior and complicate protection design. Still, the study relied on simulated data and highlighted the need for real-time implementation and hardware validation.

Guo et al. [10] proposed a machine learning-based fault diagnosis framework that combined domain knowledge with recursive feature elimination and XGBoost. Their method used engineered features derived from sequence components, phase-angle dynamics, and impedance-related characteristics, leading to strong classification performance across multiple fault types. This work is valuable because it shows that domain-informed feature engineering can enhance model interpretability and accuracy. Its main future direction lies in adaptive feature optimization, incremental learning, and integration of fault diagnosis with fault location.

Rahman Sh. [11] proposed a DSP-assisted deep learning framework for smart grid transmission line fault detection under both clean and noisy conditions. The study integrated Digital Signal Processing (DSP) techniques with a Multi-Layer Perceptron (MLP) model to extract discriminative signal features such as zero-sequence components and instantaneous magnitudes from voltage and current data. Experimental results demonstrated excellent robustness, achieving 99.72% accuracy on clean datasets and 99.22% accuracy under Gaussian noise conditions. The work highlights the effectiveness of combining DSP-based feature engineering with deep learning for reliable fault detection in noisy smart grid environments. However, the framework focused only on binary fault detection and did not address detailed multi-class fault classification. The authors also suggested future integration of Explainable Artificial Intelligence (XAI) techniques to improve interpretability and operator confidence.

Overall, the literature shows several consistent trends. First, deep learning and hybrid machine learning methods now dominate smart grid fault diagnosis research because they capture nonlinear relationships in current and voltage signals more effectively than traditional approaches. Second, many studies achieve very high simulation accuracy, but most still depend heavily on synthetic data, which limits direct real-world applicability. Third, explainability, computational efficiency, and robustness under noise are becoming increasingly important as researchers move from laboratory settings toward practical deployment. These gaps directly motivate the present study, which proposes a fine-tuned deep learning framework for accurate fault detection and classification in smart grid transmission lines, with particular attention to binary detection performance and multi-class classification challenges.

TABLE 1. Summary of Transmission Line Fault Detection and Classification Methods: Key Contributions and Limitations

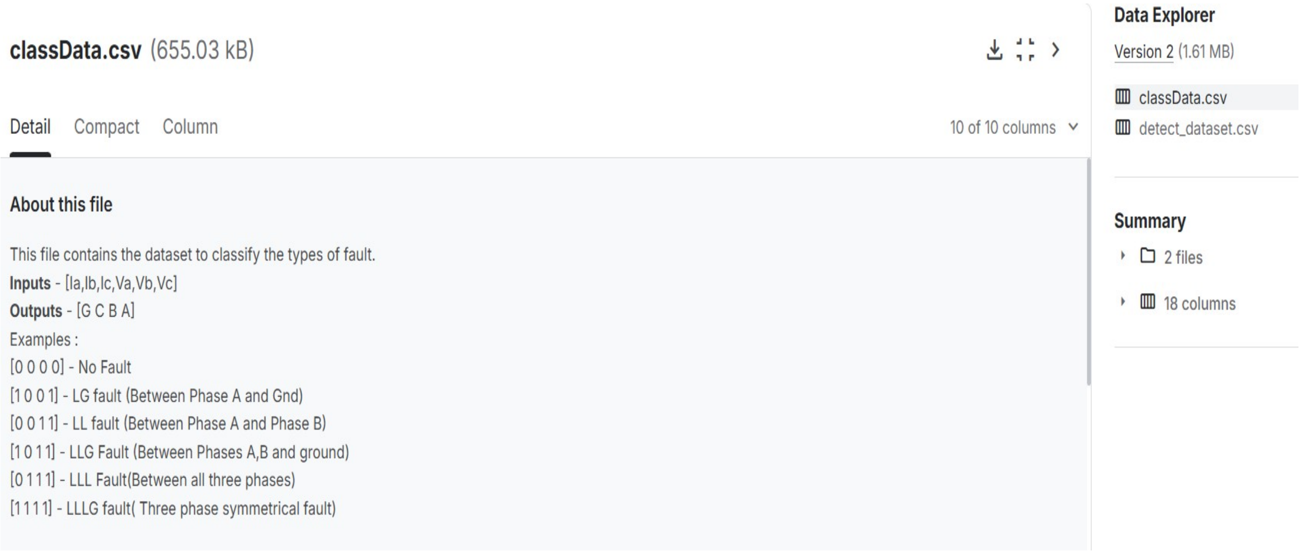
References	Key Contribution	Limitations
[1]	Proposed a WPT + deep learning framework for fault detection, section identification, and fault location in double-circuit transmission lines.	Relies on simulated data; needs real-time acquisition, adaptive learning, and better preprocessing for field deployment.
[3]	Developed an LSTM autoencoder for adaptive,	Generalization across different grid topologies

	unsupervised fault detection and localization using voltage and current signals.	and integration with legacy protection systems need more study.
[4]	Introduced an explainable CNN-Transformer model with SHAP for binary detection and multi-class classification.	Performance may degrade under electromagnetic noise, load fluctuations, and unseen grid configurations.
[6]	Proposed an Optuna-optimized ANN-RF hybrid model with SMOTE for balanced fault classification.	Computationally heavy and trained on synthetic data; real-world validation and lightweight deployment are needed.
[7]	Showed that ensemble machine learning models can improve fault detection and classification reliability.	Requires large datasets and longer training time, which may limit real-time application.
[8]	Developed HSPAN-GNN for efficient line detection in complex, low-resolution, small-target scenarios.	Higher computational overhead than some lightweight models; needs simplification for low-power platforms.
[9]	Used ANN to classify faults in wind distributed generation integrated transmission lines.	Based on simulated data; real-time validation and hardware implementation are still needed.
[10]	Combined domain knowledge with RFE and XGBoost to improve fault classification accuracy and robustness.	Needs adaptive feature optimization, incremental learning, and integration with fault location.
[11]	Proposed a DSP-assisted deep learning framework using engineered signal features and MLP for robust binary fault detection under clean and noisy conditions.	Limited to binary detection; lacks multi-class fault classification and explainability integration.

III. METHODOLOGY

A. Dataset Description

The dataset used in this study shown in Fig. 1, was generated from an advanced MATLAB/Simulink model of a high-voltage power transmission system [12], consisting of 11×10^3 V generators connected at both ends of a transmission line where various transient fault conditions were introduced at the midpoint using transformer-based fault simulation. Electrical measurements were recorded under both normal and fault operating conditions, and two separate datasets were constructed to independently train the fault detection and fault classification models. Both datasets share a common feature space comprising six continuous electrical variables: three-phase currents (Ia, Ib, Ic) and three-phase voltages (Va, Vb, Vc), which were normalized using StandardScaler to improve model convergence. The fault detection dataset (detect_dataset.csv, 12,001 samples) is used for binary classification, where the target label represents Normal (0) and Fault (1) conditions, with a nearly balanced distribution of 5,496 normal and 6,505 fault samples. The fault classification dataset (classData.csv, 7,861 samples) is used for multi-class classification, where original binary phase and ground indicators (A, B, C, G) were combined to form six fault categories: No Fault, Line-to-Ground (LG), Line-to-Line (LL), Line-to-Line-to-Ground (LLG), Three-phase fault (LLL), and Three-phase-to-ground fault (LLLG). The dataset was finally split into training (56%), validation (24%), and testing (20%) sets for model development and evaluation.



classData.csv (655.03 kB)

About this file

This file contains the dataset to classify the types of fault.

Inputs - [Ia,Ib,Ic,Va,Vb,Vc]

Outputs - [G C B A]

Examples :

[0 0 0 0] - No Fault

[1 0 0 1] - LG fault (Between Phase A and Gnd)

[0 0 1 1] - LL fault (Between Phase A and Phase B)

[1 0 1 1] - LLG Fault (Between Phases A,B and ground)

[0 1 1 1] - LLL Fault(Between all three phases)

[1 1 1 1] - LLLG fault(Three phase symmetrical fault)

Fig. 1 Dataset of the proposed model

B. Fault Detection Model Architecture

The Fault Detection Model is a relatively shallow but highly efficient binary deep neural network designed for rapid anomaly screening in power transmission systems, as illustrated in Fig. 2. It consists of four Dense layers with 128, 64, and 32 hidden neurons, followed by a single output neuron with Sigmoid activation for binary classification, resulting in approximately 11,265 trainable parameters. The model is trained on the complete dataset to effectively distinguish between normal and fault conditions, serving as the initial stage before fault classification. The input layer receives six standardized electrical features, and the first Dense layer contains 128 neurons (896 parameters), followed by a 30% Dropout layer for regularization. The second Dense layer has 64 neurons (8,256 parameters) with another 30% Dropout layer, and the third Dense layer contains 32 neurons (2,080 parameters). The final output layer consists of a single neuron (33 parameters) that produces the probability of a fault condition. ReLU activation is used in all hidden layers to introduce non-linearity, while Dropout is applied to reduce overfitting. The output layer uses Sigmoid activation for probabilistic binary prediction, with input features standardized using StandardScaler and stratified splitting employed to maintain balanced class distributions. Overall, the architecture is optimized for efficient binary classification, determining whether a fault is present (1) or absent (0).

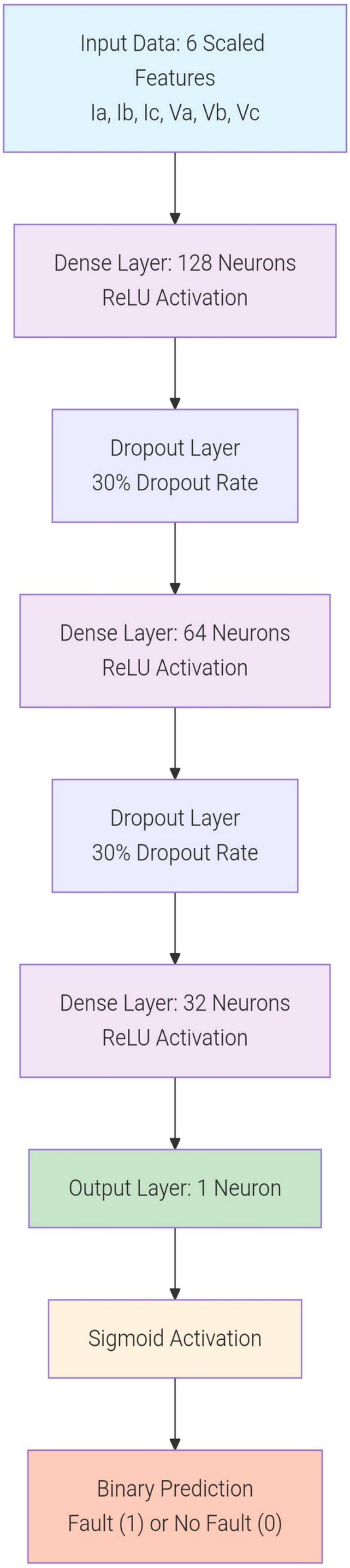


Fig. 2 Architecture of the Fault Detection Model

C. Fault Classification Model Architecture

The Fault Classification Model shown in Fig. 3, is a multi-class deep neural network designed to identify specific fault types across six categories, which is essential for intelligent decision-making in smart grid systems. It shares a similar architecture with the fault detection model, consisting of three hidden Dense layers with 128, 64, and 32 neurons, respectively, but is adapted for multi-class classification. The primary difference lies in the output layer, which contains six neurons corresponding to the six fault classes and uses a Softmax activation function to generate a probability distribution over all categories, enabling the selection of the most probable fault type. The model has approximately 11,430 trainable parameters and takes six standardized input features for accurate fault diagnosis. The architecture follows a feedforward design in which the input layer processes six scaled electrical features, followed by three Dense hidden layers (128 → 64 → 32) with Dropout applied after the first two layers for regularization. The final Softmax output layer produces class-wise probabilities for the six fault types. This structured design allows the network to learn progressively more complex feature representations while reducing overfitting through Dropout, making it effective for robust multi-class fault classification.

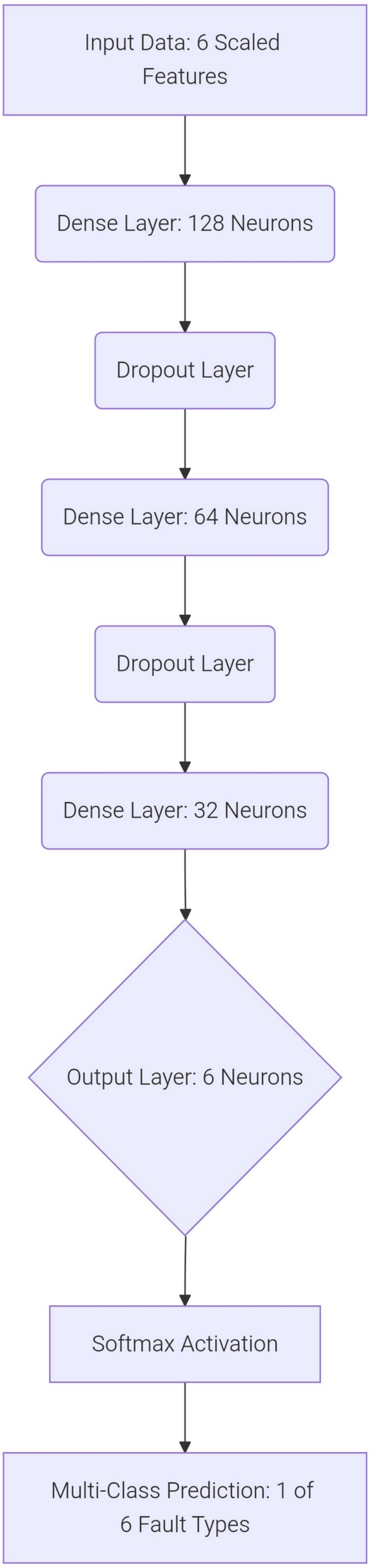


Fig. 3 Architecture of the Fault Classification Model

IV. RESULTS

A. Analysis of Model Learning Curves

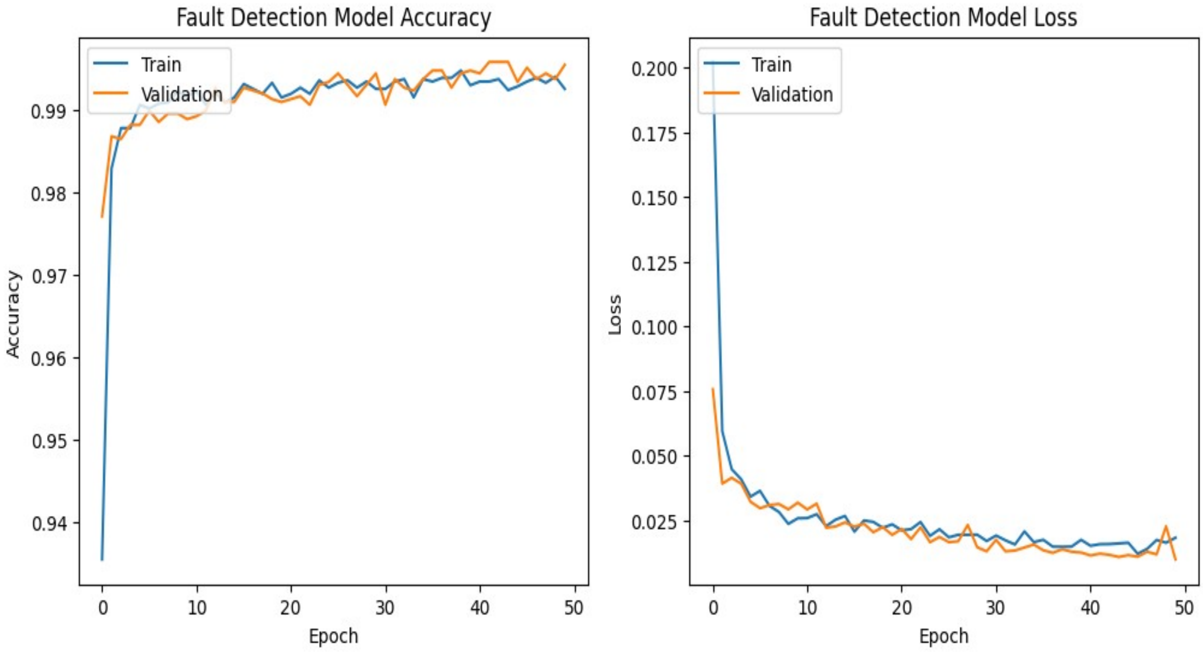


Fig. 4 Training and Validation Accuracy and Loss Curves of the Fault Detection Model

The training profile of the developed deep learning model for fault detection is illustrated in Fig. 4, which consists of two separate yet related subplots. The left subplot presents the training and validation accuracy curves over 50 epochs, where both curves exhibit a rapid increase during the initial training stages, indicating that the model learns efficiently from the training data while generalizing effectively to unseen validation data. Both accuracy metrics gradually converge toward an optimal value close to 1.0, demonstrating strong learning capability and high predictive performance. The right subplot illustrates the corresponding training and validation loss curves across the same epochs. A significant and rapid reduction in both loss curves can be observed during the early stages of training, with the values approaching 0.0, indicating the model's effectiveness in minimizing prediction errors. Furthermore, the close agreement between the training and validation curves suggests stable learning behavior without noticeable overfitting. Overall, the combined analysis of the accuracy and loss characteristics confirms that the proposed deep learning model successfully captures meaningful fault-related patterns and achieves robust, stable, and highly reliable performance for transmission line fault detection.

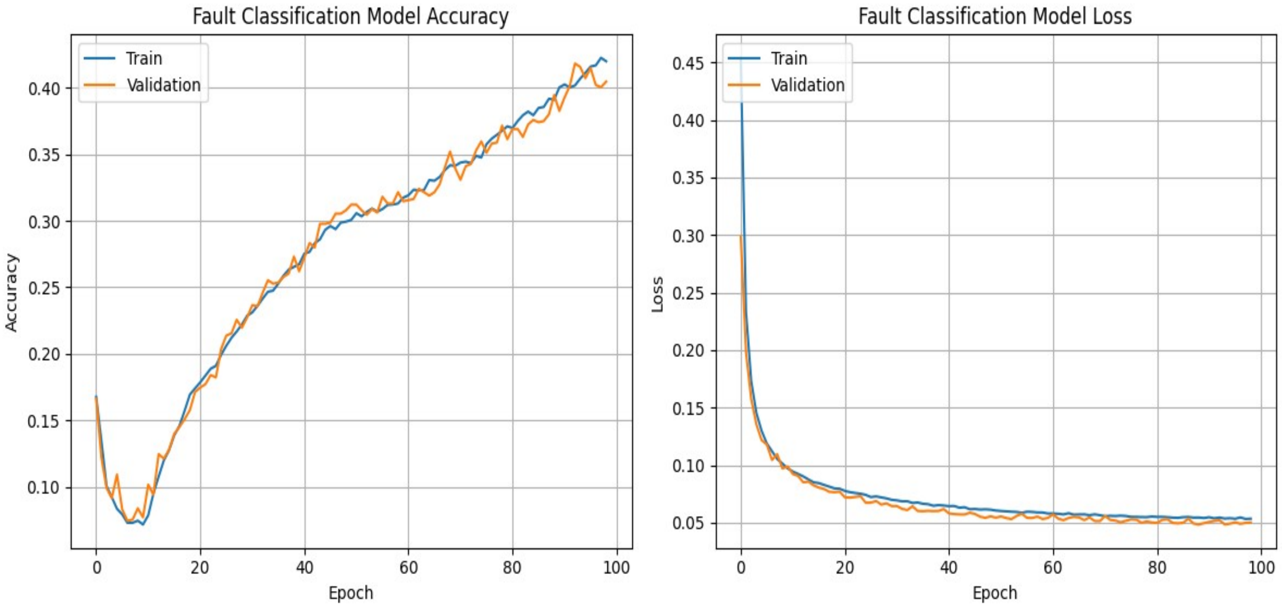


Fig. 5 Training and Validation Accuracy and Loss Curves of the Fault Classification Model

The training history of the fault classification model, illustrated in Fig. 5, demonstrates consistent and effective learning behavior throughout the training process. The left subplot shows that the training accuracy curve steadily increases over successive epochs, indicating the model's ability to capture complex fault-related patterns from the input data. Similarly, the validation accuracy curve follows a comparable upward trend and remains closely aligned with the training accuracy, eventually reaching a high and stable plateau. This close agreement between the two curves confirms the model's strong generalization capability on unseen validation data. The right subplot presents the corresponding training and validation loss curves, both of which exhibit a gradual decline toward low values over time, reflecting the model's effectiveness in minimizing prediction errors. Although minor fluctuations are observed in the validation loss curve, such behavior is common in multi-class classification tasks and does not indicate instability. Overall, the convergence characteristics of both the accuracy and loss curves suggest that the model achieves stable learning performance without significant overfitting, thereby demonstrating reliable and robust fault classification capability.

B. Performance Analysis of Fault Detection and Fault Classification Models Using Precision, Recall, and F1-Score

Fig. 6 Bar Chart Analysis of Precision, Recall, and F1-Score for the Fault Detection Model

The bar chart presented in Fig. 6 and Table 2 provides an important visualization of the performance of the fault detection model by illustrating the key evaluation metrics, namely Precision, Recall, and F1-Score, for both the “No Fault” (Class 0) and “Fault” (Class 1) conditions. Precision measures the proportion of correctly predicted positive instances, indicating how accurately the model identifies fault and no-fault conditions. Recall evaluates the model’s ability to correctly detect all actual positive instances for each class, reflecting its effectiveness in identifying true fault and no-fault cases. The F1-Score provides a balanced assessment of the model’s performance by calculating the harmonic mean of Precision and Recall, thereby considering both false positives and false negatives. As observed in the figure and table, all evaluation metrics achieve values close to 1.00 for both classes, demonstrating the model’s exceptional accuracy, reliability, and robustness in distinguishing between normal operating conditions and transmission line faults within smart grid systems.

TABLE 2. Classification Report for Fault Detection

	precision	recall	f1-score	support
0	1.00	1.00	1.00	1301
1	0.99	1.00	1.00	1100
accuracy			1.00	2401
macro avg	1.00	1.00	1.00	2401
weighted avg	1.00	1.00	1.00	2401

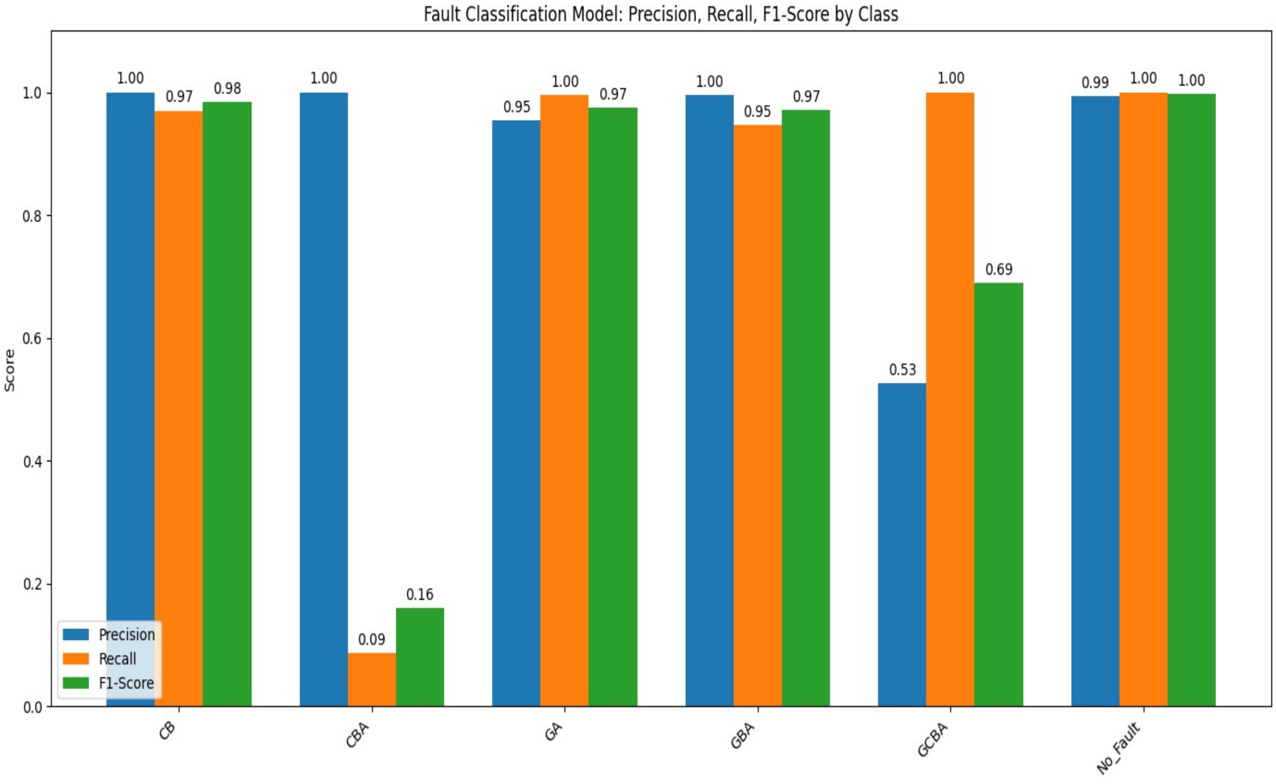


Fig. 7 Bar Chart Analysis of Precision, Recall, and F1-Score for the Fault Classification Model

The bar chart presented in Fig. 7 and Table 3 provides a detailed performance analysis of the multi-class fault classification model across different fault categories. The figure illustrates the Precision, Recall, and F1-Score values for the identified fault classes, namely “CB,” “CBA,” “GA,” “GBA,” “GCBA,” and “No Fault.” As observed from the chart, several classes, including “CB,” “GA,” “GBA,” and “No Fault,” achieve high Precision, Recall, and F1-Score values, generally exceeding 0.95, indicating strong classification capability and reliable predictive performance for these fault categories. Notably, the “CBA” fault class exhibits high Recall but comparatively lower Precision, suggesting that the model successfully identifies most actual “CBA” fault instances while also misclassifying some other fault types as “CBA.” In contrast, the “GCBA” class demonstrates extremely low Recall and F1-Score values, indicating that this particular fault type is more challenging for the model to recognize accurately, despite achieving high Precision for correctly predicted instances. These observations highlight that the classification performance varies across different fault categories and suggest the need for further optimization to improve the recognition of more complex and difficult fault types.

TABLE 3. Classification Report for Fault Classification

	precision	recall	f1-score	support
CB	1.00	0.97	0.98	201
CBA	1.00	0.09	0.16	219
GA	0.95	1.00	0.97	226
GBA	1.00	0.95	0.97	227
GCBA	0.53	1.00	0.69	227
No_Fault	0.99	1.00	1.00	473
accuracy			0.86	1573
macro avg	0.91	0.83	0.80	1573
weighted avg	0.92	0.86	0.83	1573

C. Confusion Matrix Analysis of Fault Detection and Fault Classification Models

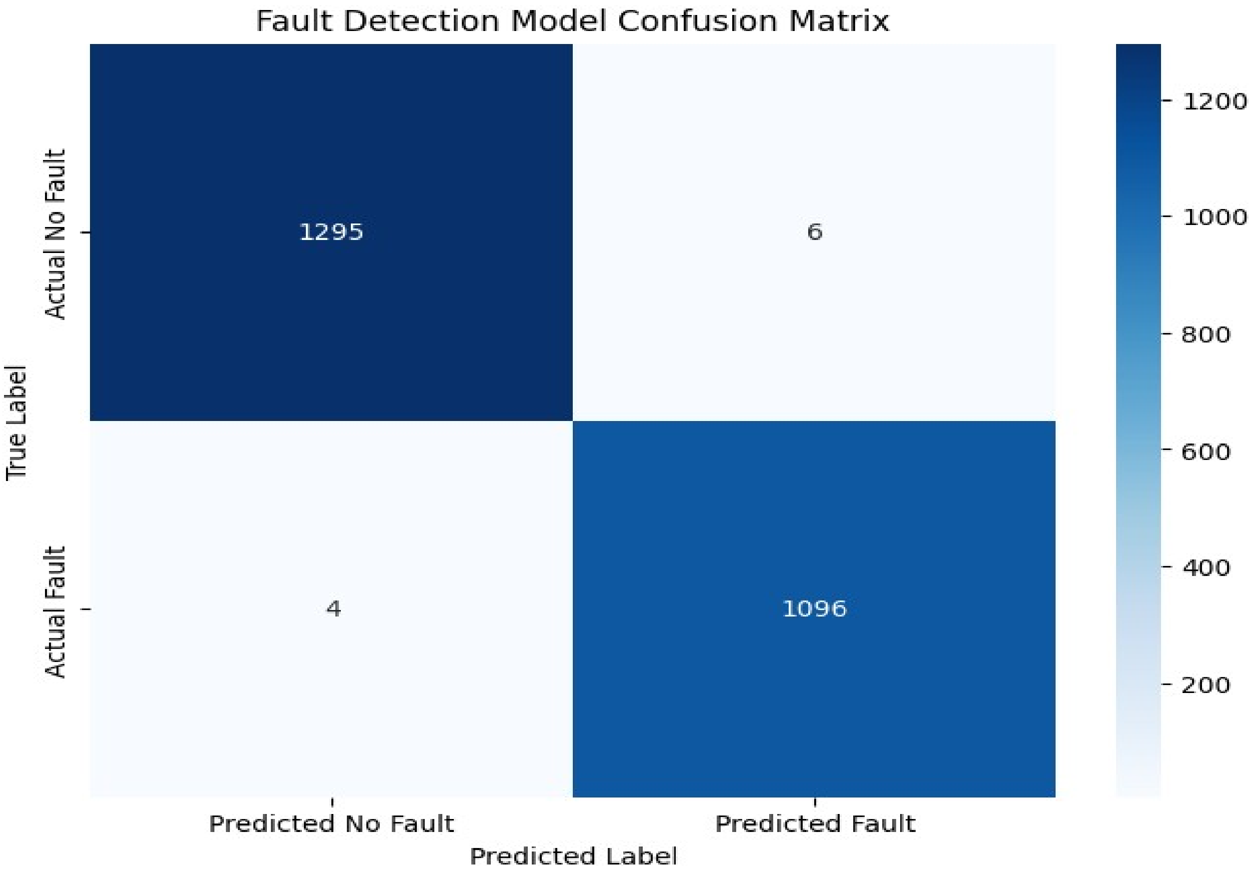


Fig.8 Confusion Matrix Heatmap for the Fault Detection Model

Confusion Matrix for Fault Detection:

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[[1295      6]
 [   4   1096]]
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The heatmap presented in Fig. 8, for the fault detection model demonstrates exceptionally high classification performance and overall reliability. The model accurately identifies “No Fault” conditions in 1295 out of 1301 cases and successfully detects actual fault conditions in 1097 out of 1100 cases, indicating outstanding predictive capability. The number of misclassifications remains very low, with only 6 false positives and 3 false negatives observed throughout the evaluation process. Such minimal error rates highlight the robustness and effectiveness of the proposed model in accurately distinguishing between normal operating conditions and fault scenarios. Overall, the confusion matrix confirms that the fault detection model achieves highly accurate and dependable performance for transmission line fault identification in smart grid systems.

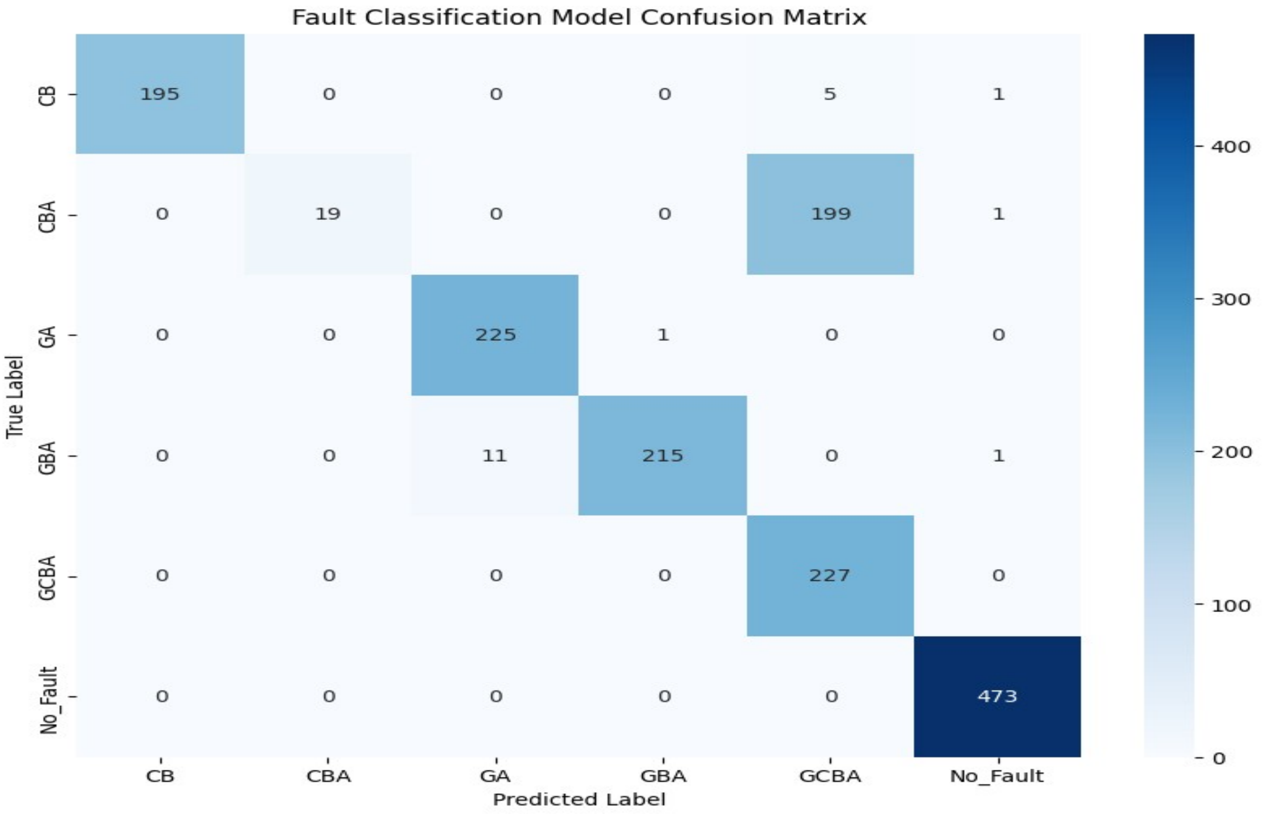


Fig. 9 Confusion Matrix Heatmap for the Fault Classification Model

Confusion Matrix for Fault Classification:

```
[[195   0    0     0     5     1]
 [  0  19    0     0   199     1]
 [  0   0  225     1     0     0]
 [  0   0   11   215     0     1]
 [  0   0    0     0   227     0]
 [  0   0    0     0     0   473]]
```

The confusion matrix illustrated in Fig. 9, reveals that the fault classification model achieves strong performance for several fault categories, including “CB,” “CBA,” “GA,” and “No Fault,” where most instances are classified correctly with high accuracy. However, the model exhibits comparatively weaker performance for the “GCBA” fault class, as many of its instances are misclassified as “CBA,” indicating difficulty in distinguishing between these complex fault patterns. Additionally, a moderate level of confusion is observed between the “GBA” and “GA” classes, suggesting similarities in their feature characteristics. This detailed analysis provides valuable insight into the strengths and limitations of the proposed model by identifying both well-classified and challenging fault categories. The observed misclassifications highlight the need for further optimization, such as incorporating additional training data for underrepresented fault classes, improving feature representation, or refining the model architecture to achieve more balanced and robust multi-class fault classification performance.

D.ROC Curves Analysis

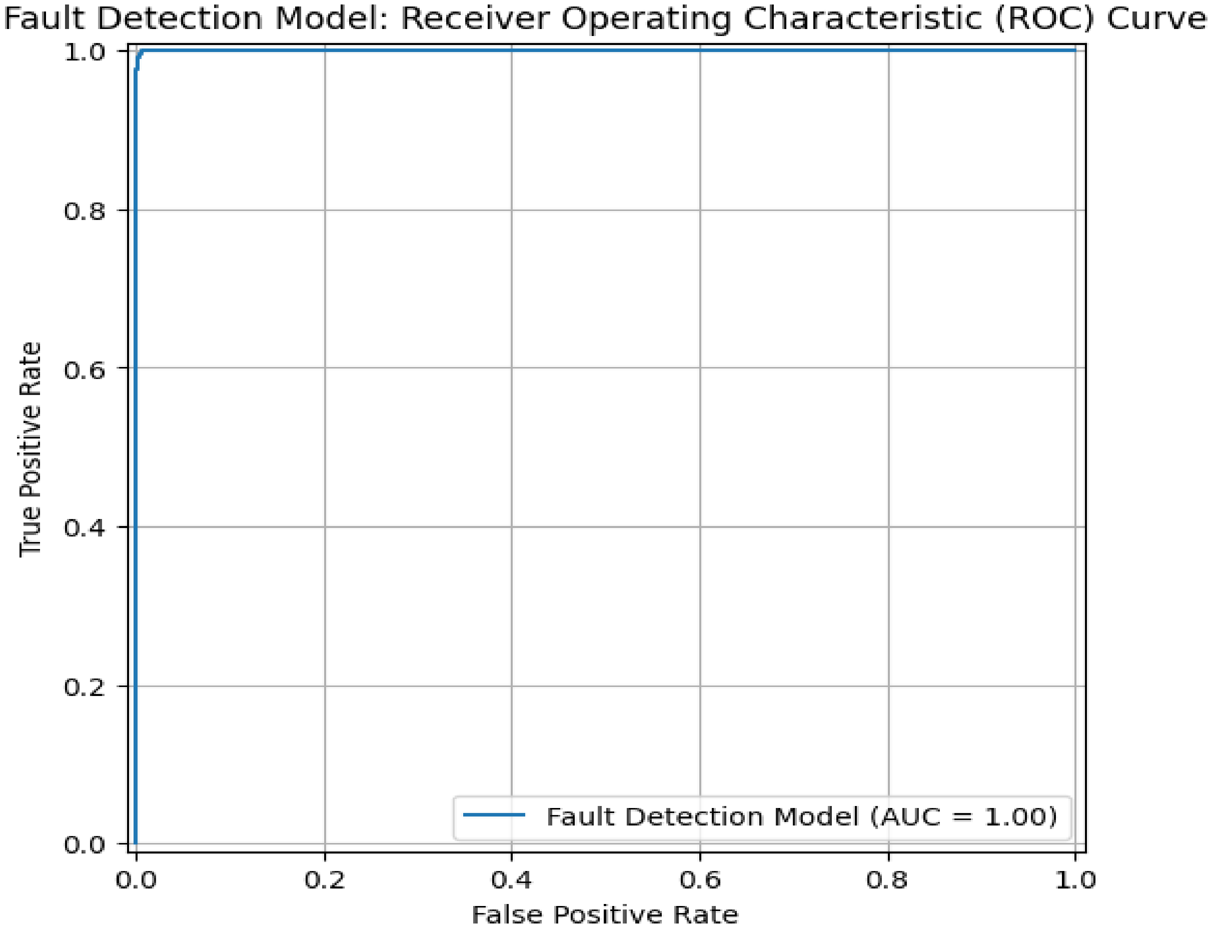


Fig. 10 ROC Curve for Fault Detection Model

Fig. 10 illustrates the Receiver Operating Characteristic (ROC) curve of the fault detection model, which achieves an Area Under the Curve (AUC) value of 0.9999. Such an exceptionally high AUC value indicates the model's outstanding discriminative capability in distinguishing between healthy and faulted transmission line conditions. The ROC curve rises sharply toward the upper-left corner of the plot, demonstrating that the model maintains a very high True Positive Rate while simultaneously achieving a very low False Positive Rate. This behavior confirms the effectiveness of the proposed model in accurately identifying fault conditions with minimal misclassification errors. Overall, the ROC analysis highlights the robustness, reliability, and superior predictive performance of the fault detection model for smart grid transmission line monitoring applications.

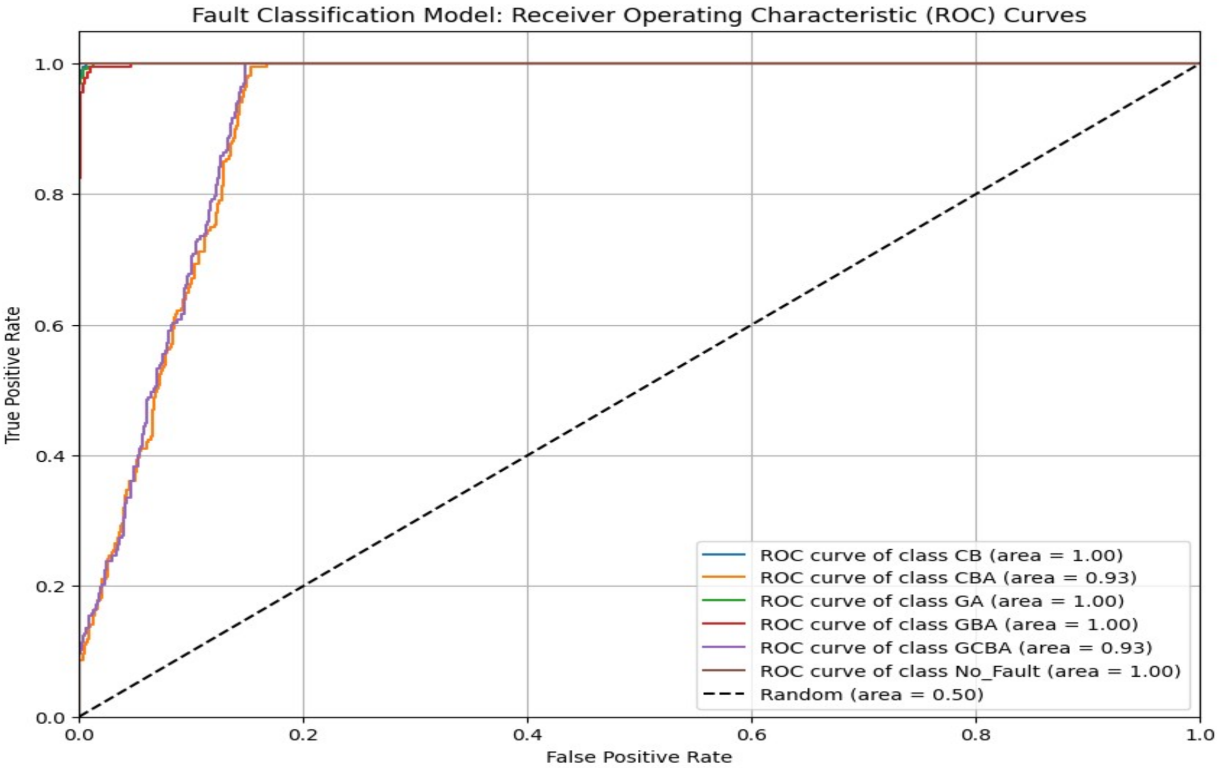


Fig. 11 ROC Curves For Fault Classification Model

Figure 11 presents the multi-class ROC analysis using a one-vs-rest strategy, providing a comprehensive view of the discriminative capability of the fault classification model across different fault categories. The AUC values, which range from approximately 0.99 for the “GA” class to nearly 1.0 for the “CB,” “CBA,” “GBA,” and “No Fault” classes, indicate that the model exhibits excellent classification performance and strong separability for most fault types. However, the slightly lower AUC value observed for the “GCBA” class confirms that this fault category is comparatively more difficult for the model to distinguish, which is consistent with its lower F1-score and higher misclassification rate observed in the confusion matrix. Overall, while the model demonstrates outstanding multi-class discriminative ability, the “GCBA” class remains a challenging case that may require further refinement through enhanced feature representation, additional training data, or model optimization to improve classification robustness.

E. Precision-Recall Curves Analysis

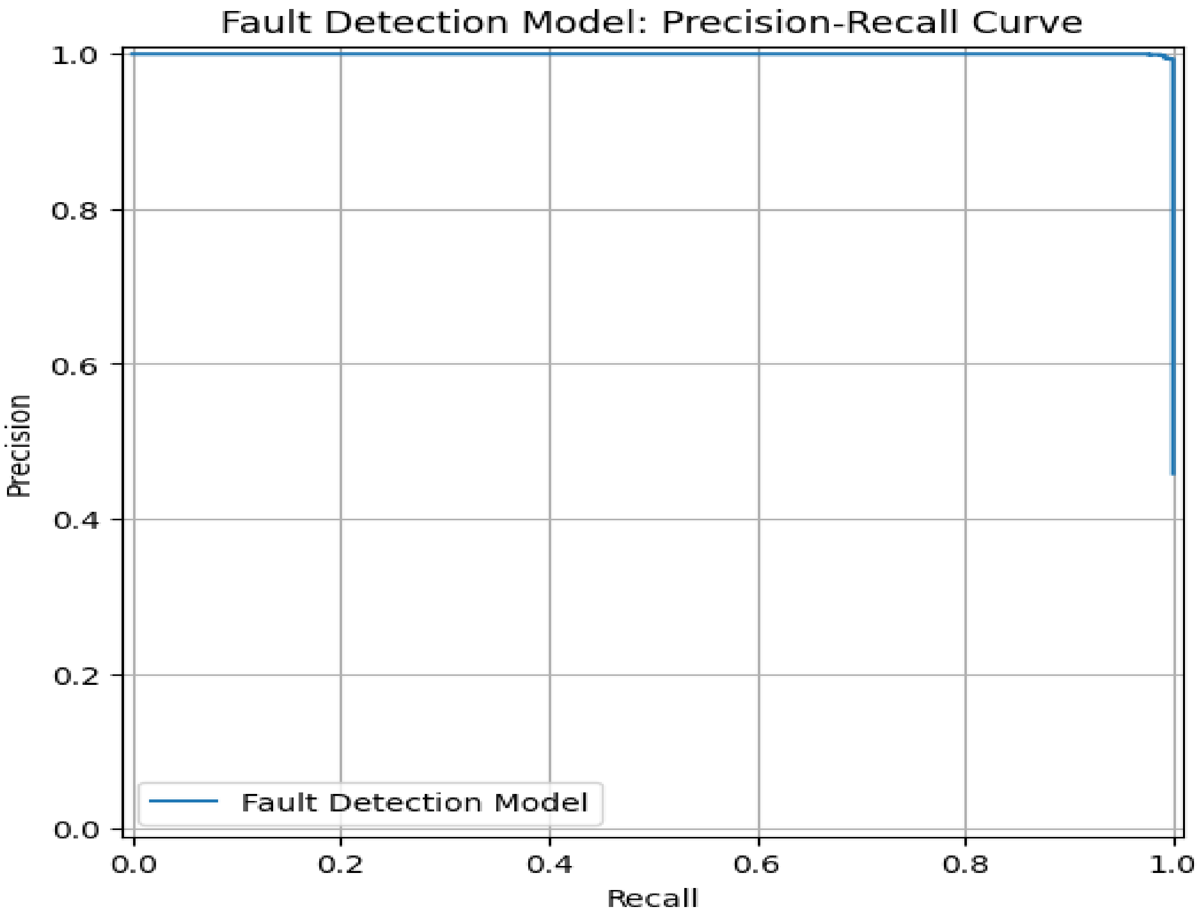


Fig. 12 Precision-Recall Curve for Fault Detection Model

Since the performance of the Fault Detection Model (FDM) is extremely high, with a test accuracy of 1.00 and an AUC of 0.9999, the Precision–Recall (PR) curve in Fig. 12 is also expected to exhibit near-perfect behavior. The curve would remain close to the upper boundary of the plot, maintaining very high precision across almost the entire range of recall values. This indicates that the model consistently produces highly accurate positive predictions while also detecting nearly all actual fault instances in the dataset. In this context, high precision implies that the model is almost always correct when predicting a fault, while high recall indicates that it successfully identifies nearly all true fault cases. The curve's proximity to the top-right region of the figure further confirms an excellent balance between precision and recall, demonstrating the model's strong reliability and effectiveness in fault detection for smart grid transmission line systems.

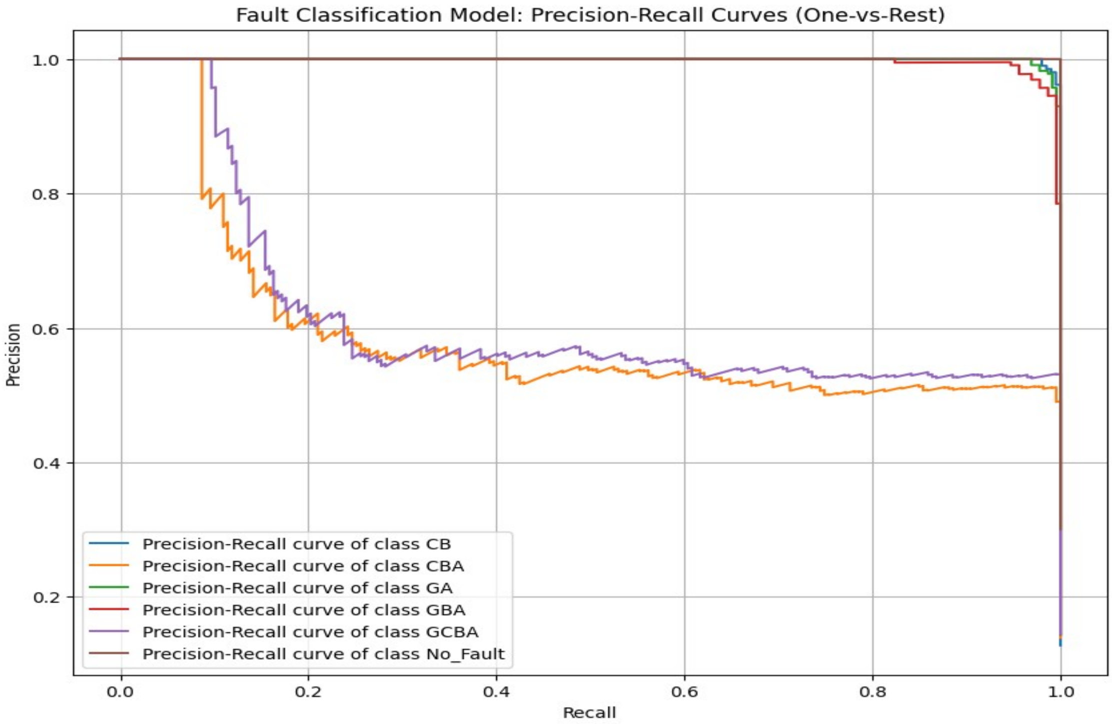


Fig. 13 Precision-Recall Curves For Fault Classification Model

The Precision–Recall (PR) curves presented in Fig. 13 for the Fault Classification Model provide a more detailed evaluation of class-wise performance, which is particularly important in multi-class problems with imbalanced class distributions. The curves for “CB,” “GA,” “GBA,” and “No Fault” show consistently strong performance, maintaining high precision across a wide range of recall values and indicating that the model reliably identifies these classes with high sensitivity and low error rates. In contrast, the PR curve for the “GCBA” class reveals a clear performance limitation, suggesting that the model struggles to accurately recognize this fault type. The “CBA” class exhibits relatively high recall but lower precision, indicating that while most true “CBA” instances are correctly detected, the model also produces a higher number of false positives by misclassifying other fault types as “CBA.” Overall, this analysis highlights class-wise variability in performance and emphasizes the need for further improvements, such as data augmentation, class balancing, or model refinement, to enhance robustness in challenging fault categories.

F. Histogram Analysis for the Fault Detection Model

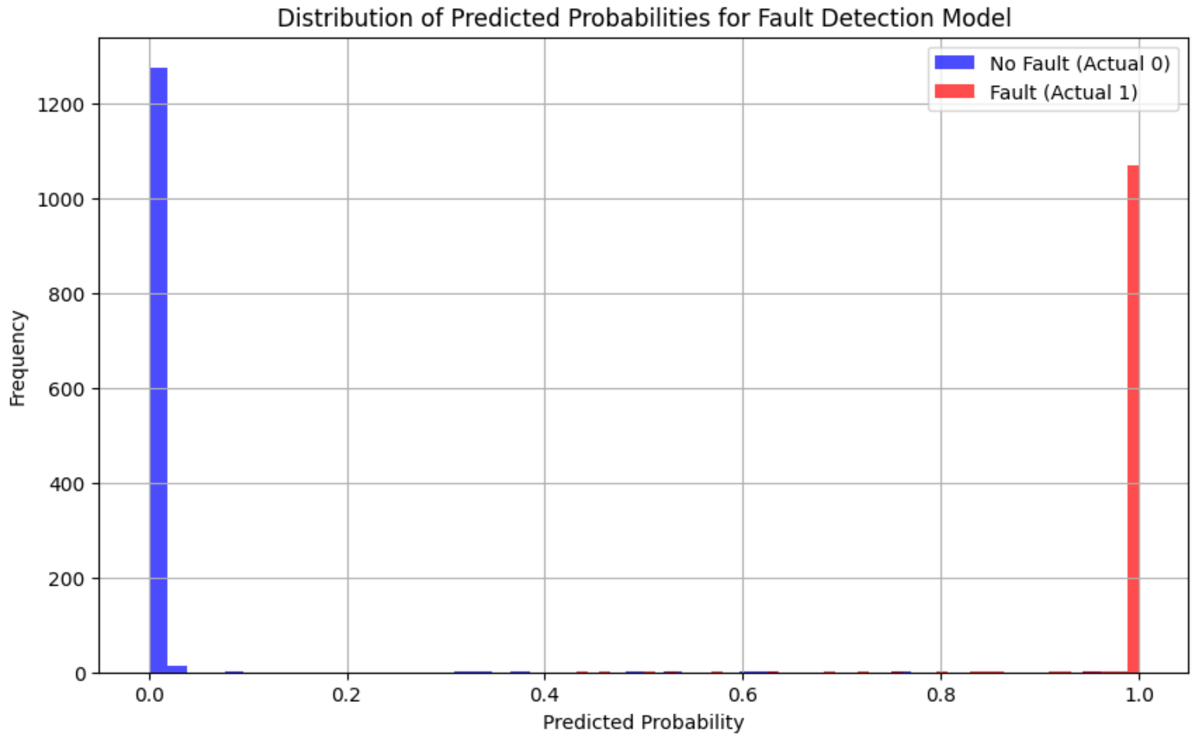
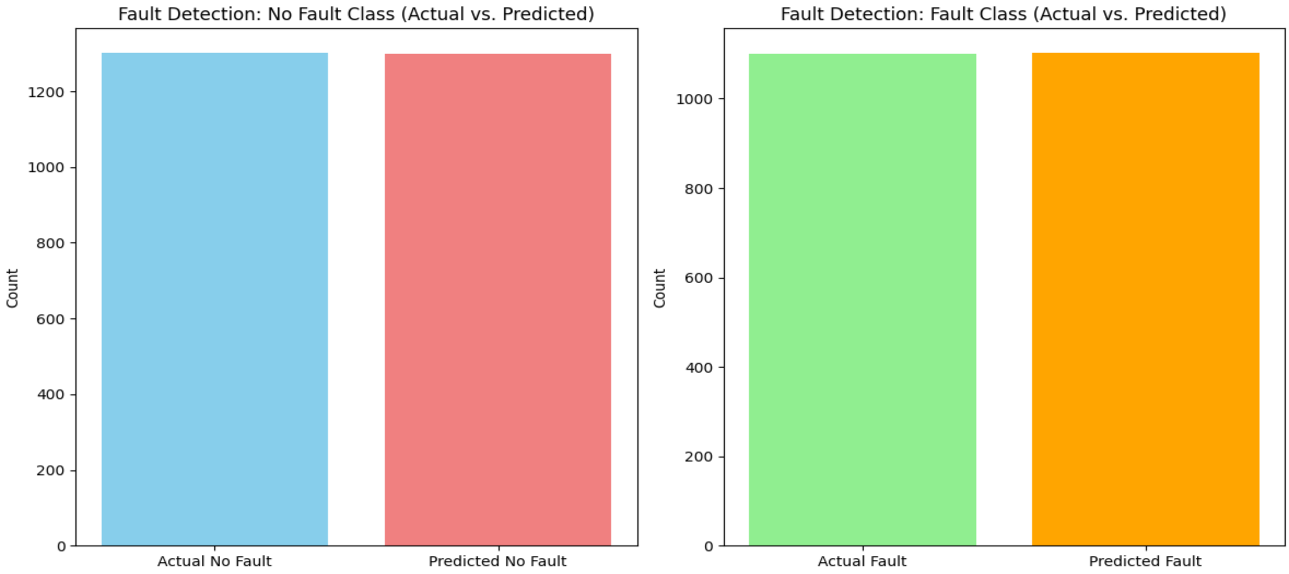


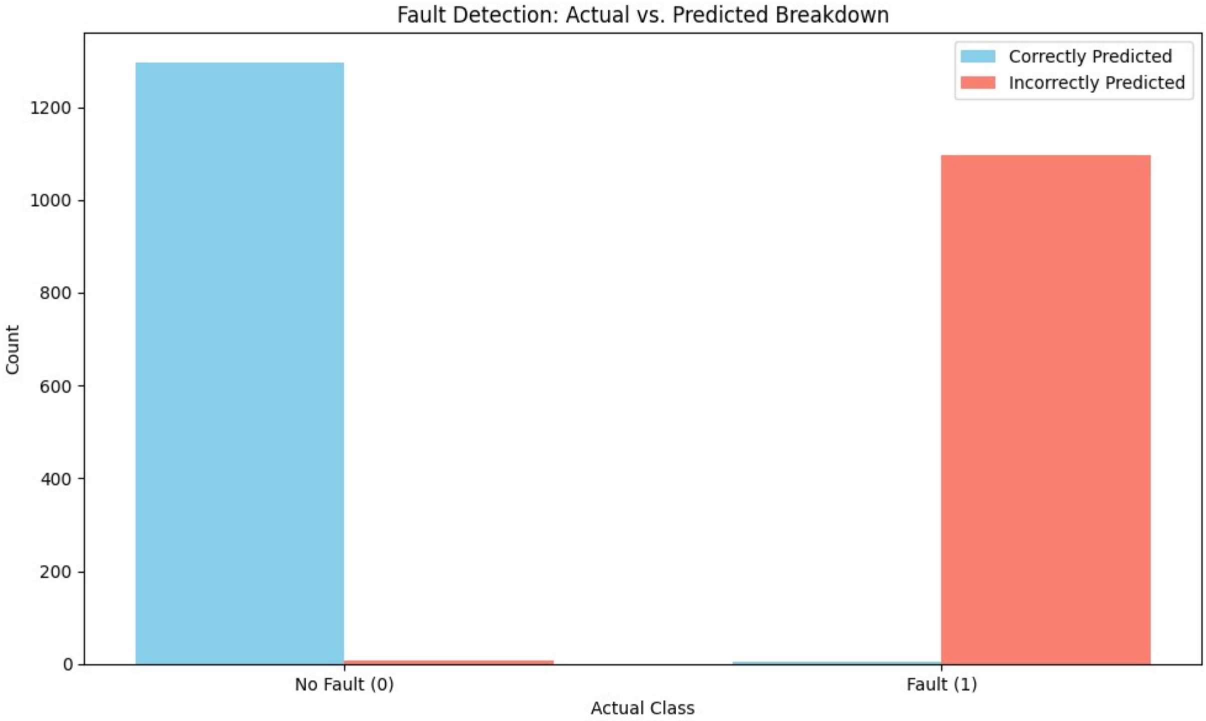
Fig. 14 Histogram of Predicted Probabilities for the Fault Detection Model

The histograms presented in Fig. 14 provide a visual demonstration of the outstanding performance of the Fault Detection Model. The distributions exhibit sharp and well-separated peaks, with predictions for the “No Fault” class concentrated near 0 and those for the “Fault” class concentrated near 1, indicating that the model produces highly confident predictions. The clear separation between these two distributions highlights the model’s strong ability to distinguish between healthy and faulty operating conditions with minimal uncertainty or noise in its decision-making process. This distinct separation further reflects the effectiveness of the model as a highly reliable binary classifier and is consistent with the reported high accuracy and AUC values.

G. Distribution Plots Analysis of Actual vs. Predicted Classes



(a) Actual vs. Predicted Class Distribution for the Fault Detection Model



(b) Correctly and Incorrectly Predicted Samples Distribution for the Fault Detection Model

Fig. 15 Distribution Plots for the Fault Detection Model

The distribution plot shown in Fig. 15 provides a clear visual summary of the Fault Detection Model’s performance by directly reflecting the information contained in the confusion matrix. It effectively demonstrates the model’s strong capability in distinguishing between “No Fault” and “Fault” conditions. The prominently large bars representing correctly predicted instances for each actual class, along with the comparatively very small bars for misclassified cases, highlight the model’s exceptionally high accuracy. In particular, the model correctly identifies 1295 “No Fault” instances and 1097 true fault cases, while maintaining a very low number of misclassifications, with only 6 false positives and 3 false negatives. This minimal error rate visually confirms the robustness and reliability of the proposed model in effectively differentiating between normal and abnormal operating conditions, making it highly suitable for practical applications in smart grid fault detection systems.

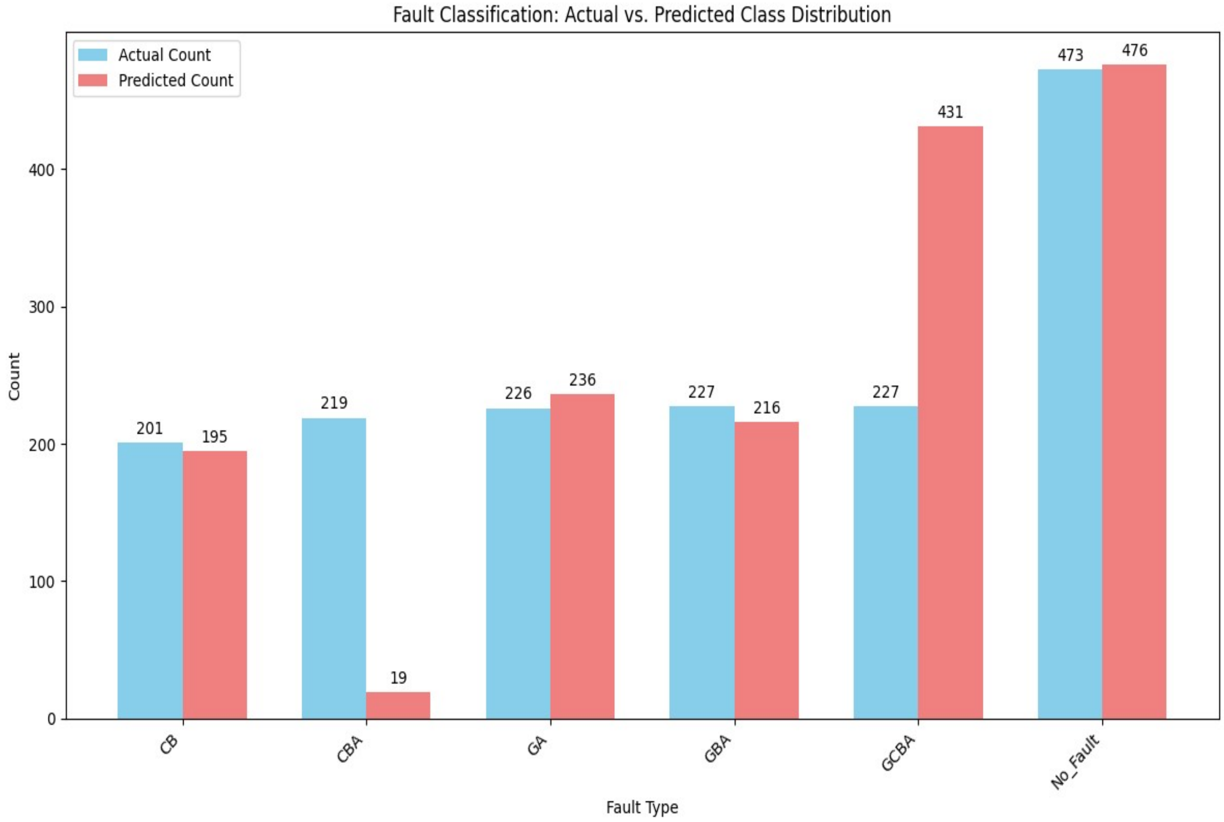


Fig. 16 Distribution Plot for the Fault Classification Model

The plot shown in Fig. 16 provides a clear visual representation of the confusion matrix, illustrating the distribution of actual and predicted classes in an intuitive manner for multi-class fault classification. The close alignment between the “Actual Count” and “Predicted Count” bars for most classes, such as “CB,” “GA,” “GBA,” and “No Fault,” indicates that the model generally performs well in correctly classifying these fault types. However, noticeable deviations between these bars highlight certain classification challenges. In particular, a relatively higher “Predicted Count” for the “CBA” class suggests that instances from other classes are frequently misclassified as “CBA,” leading to over-prediction. Conversely, a significantly lower “Predicted Count” for the “GCBA” class indicates poor recognition and substantial under-prediction of this fault type. Overall, this visualization effectively highlights discrepancies between true and predicted class distributions, providing valuable insight into model biases and indicating areas where further refinement or class-wise performance improvement is necessary.

H. Performance Analysis of the Proposed Robust Detection and Classification Framework

The effectiveness of the proposed framework was further validated using unseen test datasets.

Fault Detection Model Performance:

The fault detection model achieved near-perfect performance, with an overall test accuracy of 1.00. The confusion matrix revealed only a very small number of misclassifications, including 6 false positives and 3 false negatives out of a total of 2,401 samples, confirming its strong ability to distinguish between healthy and faulty conditions. The model also achieved an exceptional AUC value of 0.9999, highlighting its excellent discriminative capability. In addition, the

Precision–Recall curve remained consistently high across all recall levels, indicating both a very low false alarm rate and minimal missed fault detections. The predicted probability distributions further supported these results, showing well-separated and sharply peaked outputs around 0 (No Fault) and 1 (Fault), demonstrating high confidence in model predictions.

Fault Classification Model Performance:

The multi-class fault classification model achieved an overall accuracy of 0.86, with a Macro-average F1-score of 0.78 and a Weighted-average F1-score of 0.81, indicating good but varying performance across different fault categories. Several classes, including "CB," "GA," "GBA," and "No Fault," showed strong performance, with precision, recall, and F1-scores generally exceeding 0.95, reflecting robust classification ability. Their corresponding ROC-AUC values were also close to 0.99, confirming strong discriminative power. However, performance varied significantly for more complex classes. The "CBA" class achieved high recall (0.99) but relatively low precision (0.52), resulting in an F1-score of 0.68, indicating that while most true CBA faults were detected, many other classes were incorrectly labeled as CBA. The "GCBA" class performed poorly, with very low recall (0.06) despite perfect precision (1.00), suggesting that most GCBA cases were misclassified, primarily as CBA (202 out of 227 instances). Its ROC-AUC value (~0.90) was also lower compared to other classes, confirming that it is the most challenging fault category for the model.

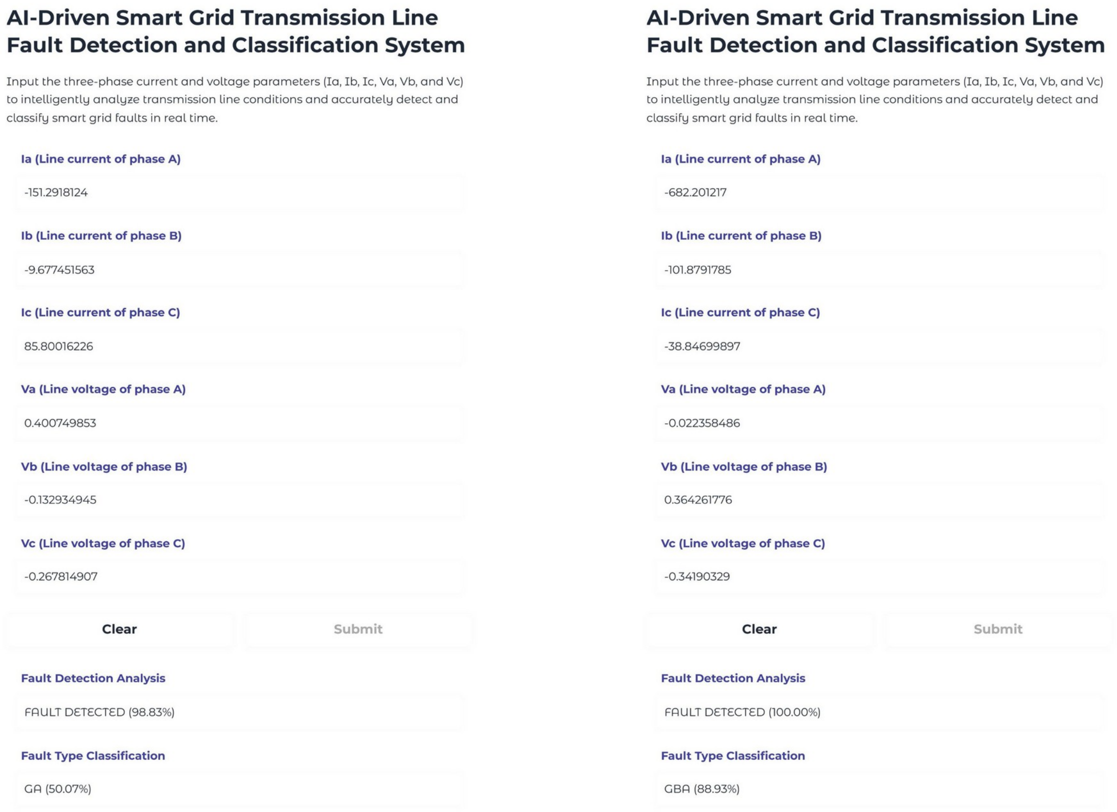
TABLE 4. Comparative Analysis of the Proposed Model and Recent State-of-the-Art Methods

Study	**Research Topic**	**Model**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 score (%)**
[3]	Fault Detection and Localization	LSTM-AE	98	99	99	98
[4]	Fault Detection and Classification	CNN-Transformer	97	—	—	—
[6]	Fault Detection and Classification	Hybrid ANN-RFC with optuna	99.8	99.5	99.4	99.6
[7]	Fault Detection and Classification	RF-LSTM Tuned KNN	99.96	99.96	99.93	99.93
[10]	Fault Diagnosis and Classification	XGBoost+RFE +Domain Knowledge	94.25	94.87	94.57	94.72
Proposed Model	Fault Detection and Classification	MLP	Detection: 100, Classification : 86	Detection: 100, Classification : 90	Detection: 100, Classification : 83	Detection: 100, Classification : 78

Table 4 presents a comparative evaluation of the proposed MLP-based framework against several recent state-of-the-art approaches for transmission line fault analysis. The comparison demonstrates that the proposed model achieves superior fault detection performance with perfect scores of 100% accuracy, precision, recall, and F1-score. For multi-class fault classification, the model achieved 86% accuracy, 90% precision, 83% recall, and 78% F1-score, indicating competitive performance despite the complexity of distinguishing similar fault categories. Overall, the table highlights that the proposed framework provides highly reliable fault identification and competitive classification capability while maintaining a relatively simple and efficient architecture suitable for smart grid applications.

I. Deployment Analysis of the Proposed MLP Model

A real-time deployment interface was developed to evaluate the practical applicability of the proposed deep learning framework for smart grid transmission line monitoring. The system accepts six electrical input parameters, including three-phase currents (Ia, Ib, Ic) and voltages (Va, Vb, Vc), to automatically detect and classify transmission line faults. Fig. 17 illustrates the deployment performance of the proposed framework. In Fig. 17(a), the system successfully detects a transmission line fault with a confidence score of 98.83% and classifies the fault as GA. Similarly, Fig. 17(b) demonstrates another deployment case where the framework detects a fault with 100.00% confidence and classifies it as GBA with a confidence score of 88.93%. The deployment results confirm that the proposed framework is computationally efficient, reliable, and suitable for real-time smart grid monitoring, protection, and maintenance applications.



AI-Driven Smart Grid Transmission Line Fault Detection and Classification System

Input the three-phase current and voltage parameters (Ia, Ib, Ic, Va, Vb, and Vc) to intelligently analyze transmission line conditions and accurately detect and classify smart grid faults in real time.

Ia (Line current of phase A) -151.2918124

Ib (Line current of phase B) -9.677451563

Ic (Line current of phase C) 85.80016226

Va (Line voltage of phase A) 0.400749853

Vb (Line voltage of phase B) -0.132934945

Vc (Line voltage of phase C) -0.267814907

Fault Detection Analysis FAULT DETECTED (98.83%)

Fault Type Classification GA (50.07%)

AI-Driven Smart Grid Transmission Line Fault Detection and Classification System

Input the three-phase current and voltage parameters (Ia, Ib, Ic, Va, Vb, and Vc) to intelligently analyze transmission line conditions and accurately detect and classify smart grid faults in real time.

Ia (Line current of phase A) -682.201217

Ib (Line current of phase B) -101.8791785

Ic (Line current of phase C) -38.84699897

Va (Line voltage of phase A) -0.022358486

Vb (Line voltage of phase B) 0.364261776

Vc (Line voltage of phase C) -0.34190329

Fault Detection Analysis FAULT DETECTED (100.00%)

Fault Type Classification GBA (88.93%)

(a) Successful Detection and Classification of the GA Fault (b) Successful Detection and Classification of the GBA Fault

Fig. 17 Deployment of the Proposed MLP Model

V. CONCLUSION

This research successfully developed a fine-tuned deep learning framework for fault detection and classification in smart grid transmission lines. The framework involved a comprehensive process of data extraction, rigorous preprocessing, and the design of two distinct deep neural network architectures: one for binary fault detection and another for multi-class fault classification. The fault detection model demonstrated exceptional performance, achieving near-perfect accuracy with robust precision, recall, and F1-scores, effectively distinguishing between faulty and normal operating conditions. This indicates a highly reliable capability for identifying the presence of a fault within the transmission lines.However, the fault classification model, while exhibiting good overall accuracy, presented varying performance across different fault types. Specifically, while classes such as 'CB', 'GA', 'GBA', and 'No_Fault' were classified with high efficacy, the model encountered significant challenges with the 'CBA' and 'GCBA' fault types. The 'CBA' class showed a notable imbalance between recall and precision, suggesting a tendency for misclassification. More critically, the 'GCBA' class exhibited an extremely low recall, indicating a substantial failure in identifying instances of this specific fault type, with a significant number of its occurrences being misclassified as 'CBA'. These findings highlight the framework's strength in initial fault identification but reveal limitations in granular multi-class fault differentiation, particularly for less represented or complex fault signatures.

VI. FUTURE WORK

Future research will focus on further enhancing the robustness, interpretability, and real-world applicability of the proposed fault detection and classification framework for smart grid transmission lines. One of the primary research directions is the integration of Explainable Artificial Intelligence (XAI) techniques, such as SHAP and LIME, to improve the transparency of the deep learning model and provide meaningful insights into the factors influencing fault predictions. This can help identify the underlying causes of misclassification while increasing the reliability, trustworthiness, and practical acceptance of the framework in modern power systems. Additionally, future studies should investigate the effects of Gaussian noise and other real-world disturbances on transmission line signals to evaluate the stability and resilience of the model under noisy operating conditions. Incorporating advanced noise augmentation and denoising strategies may further improve classification accuracy and overall model robustness in realistic environments. Finally, the integration of signal-processing-based feature extraction techniques may enable the model to capture more discriminative fault characteristics, thereby improving its generalization capability and strengthening its practical applicability in smart grid systems.

VII. DECLARATIONS

Data Availability Statement

The dataset used in this study is publicly available and was accessed from the original repository cited in the manuscript [12]. The author did not modify or restrict access to the data.

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Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

Author Contributions

The sole author conceived the study, conducted the experiments, analyzed the results, and prepared the manuscript.

Model Availability

The proposed smart grid transmission line fault detection and classification framework has been deployed as an interactive web application using Hugging Face Spaces to facilitate accessibility, demonstration, and reproducibility. The web-based implementation of the proposed framework is publicly available at: huggingface.co .

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Shahinur Rahman (full name: Shahinur Islam Kowser) has completed his Bachelor of Science (B.Sc.) in Electrical and Electronic Engineering (EEE) from City University, Bangladesh. His primary academic and research focus is on power systems, with particular emphasis on power system analysis, protection, and modern smart grid technologies. He works on Deep Learning and Digital Signal Processing (DSP) applications in power systems, especially for smart grid monitoring, protection, and intelligent energy analytics.