DSP-Assisted Deep Learning for Transmission Line Fault Detection in Smart Grids Under Clean and Noisy Conditions

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Abstract— This paper presents a deep learning-based fault detection system for smart grid transmission lines, addressing the critical need for robust and accurate fault identification to ensure grid stability and reliability. The proposed methodology integrates Digital Signal Processing (DSP) techniques for comprehensive feature extraction from raw current and voltage signals. Key DSP features, including instantaneous zero-sequence components, total magnitudes, and maximum instantaneous values, were derived to characterize various fault conditions. A multi-layer perceptron (MLP) deep learning model was then developed and trained on these engineered features.On a clean dataset, the model achieved exceptional performance with a test accuracy of 99.72%, and near-perfect precision, recall, and F1-scores of 1.00 for both fault and no-fault classes, as evidenced by a confusion matrix showing only 5 misclassifications out of 1801 samples. To assess robustness, the system was further evaluated using data augmented with Gaussian noise (mean=0, std=0.1). When retrained and tested on noisy data, the model maintained high performance, achieving a test accuracy of 99.22% and consistent precision, recall, and F1-scores of 0.99 across classes. This demonstrates the model's resilience to typical measurement uncertainties. The findings underscore the efficacy of combining DSP-engineered features with deep learning for highly accurate and robust fault detection in complex smart grid environments.

Keywords—Smart Grids, Fault Detection, Deep Learning, Digital Signal Processing, Robustness to Noise

I. INTRODUCTION

Smart grid transmission systems play a fundamental role in ensuring the continuous, stable, and efficient delivery of electrical energy across modern power networks. However, transmission lines are inherently vulnerable to various types of faults caused by environmental conditions, equipment degradation, lightning strikes, and operational disturbances. These faults can lead to severe consequences, including system instability, cascading failures, and large-scale power outages. Therefore, the development of accurate and real-time fault detection (FD) mechanisms is critical for enhancing grid reliability and operational resilience [1].

Traditional fault detection techniques, including impedance-based methods, relay protection schemes, and signal thresholding approaches, often rely on predefined models and assumptions about system behavior. While effective under ideal conditions, these methods struggle to maintain accuracy in dynamic smart grid environments characterized by nonlinearities, high penetration of renewable energy sources, and noisy measurements [2]. Moreover, conventional signal processing techniques such as Fourier Transform and wavelet-based analysis require careful parameter tuning and may fail to generalize across diverse fault scenarios.

Recent advancements in machine learning and deep learning have introduced data-driven approaches capable of learning complex patterns directly from electrical signals. For instance, deep neural networks, including LSTM autoencoders and graph neural networks, have demonstrated promising results in detecting anomalies and faults in transmission systems with high accuracy and adaptability [3], [4]. These approaches leverage temporal and spatial dependencies in voltage and current signals, enabling improved detection performance compared to traditional techniques. However, purely deep learning-based models often depend heavily on large datasets and may suffer from reduced interpretability and robustness, particularly under noisy or corrupted measurement conditions.

To address these limitations, hybrid approaches that integrate digital signal processing (DSP) with deep learning have gained increasing attention. DSP-based feature engineering can extract meaningful physical characteristics from raw signals, such as sequence components, magnitude variations, and transient behaviors, which enhance the discriminative capability of learning models. Recent studies have shown that combining engineered signal features with machine learning frameworks improves detection accuracy while reducing model complexity and training requirements [2], [5]. Furthermore, incorporating noise-aware evaluation has become essential, as real-world smart grid data is often affected by sensor inaccuracies and communication disturbances.

Motivated by these challenges, this paper proposes a DSP-assisted deep learning framework for transmission line fault detection in smart grids, focusing on both clean and noisy operating conditions. The proposed approach leverages carefully designed DSP-based features and a multilayer perceptron (MLP) model to achieve high detection accuracy and robustness. Unlike many existing works that emphasize fault classification or localization, this study specifically targets reliable fault detection, which is a critical first step in automated protection systems. The effectiveness of the proposed method is validated through extensive experiments, demonstrating strong performance even in the presence of Gaussian noise, thereby highlighting its practical applicability in real-world smart grid environments.

II. LITERATURE REVIEW

Recent advancements in smart grid fault detection have increasingly leveraged deep learning (DL), machine learning (ML), and hybrid signal processing techniques to improve detection accuracy, robustness, and real-time applicability.

Zhang et al. [1] proposed an advanced HSPAN-GNN model integrating graph convolution and convolutional operations for transmission line fault detection. Their model introduces a high-priority subsampling mechanism to balance computational efficiency and detection performance. Additionally, the Space-to-Depth Convolution (SPD-Conv) improves detection in low-resolution and small-target scenarios, while the Normalization-based Attention Module (NAM) enhances feature representation. Despite achieving high detection accuracy, the model suffers from computational redundancy and requires optimization techniques such as pruning or quantization for deployment in resource-constrained environments.

Hariharan et al. [2] explored hybrid machine learning approaches combined with generative AI for fault detection in smart distribution grids. Their study highlights the importance of synthetic data generation using GANs to overcome data scarcity and improve model scalability. The use of autoencoders demonstrated strong performance in detecting unseen fault patterns. However, limitations remain in capturing stochastic variations of renewable energy sources and the lack of validation on large-scale real-world systems.

Ullah et al. [3] focused on fault analysis and prediction using LSTM networks in combination with traditional Mho relay systems. Their work demonstrates that LSTM models can effectively predict transmission line parameters and assist in fault detection across varying distances. However, the study relies heavily on simulated data and lacks validation under real-world noisy conditions, which is critical for practical deployment.

Hossain et al. [4] introduced an LSTM autoencoder-based unsupervised fault detection framework capable of learning normal operational patterns and identifying anomalies. The model achieves high accuracy (98%) and strong robustness against noise (maintaining F1-score above 92% at 20 dB SNR). While the approach shows promise for real-time applications, its performance depends on diverse training data and requires further validation across different grid topologies and hardware environments.

Ali and Esmail [6] proposed a hybrid Wavelet Packet Transform (WPT) and deep learning framework for fault diagnosis in double-circuit transmission lines. The WPT extracts meaningful signal features, which are then processed by DL models for fault classification and localization. Their method achieves high precision with minimal error (0.03%), demonstrating the effectiveness of combining DSP techniques with DL. However, real-time implementation and adaptive learning capabilities remain open challenges.

Uzel et al. [7] developed an optimized ANN-RF hybrid model enhanced with Optuna hyperparameter tuning and SMOTE for class balancing. The model achieved 99.8% accuracy and strong classification performance across multiple fault types. Nevertheless, the approach suffers from computational complexity and dependence on synthetic datasets, limiting its real-world applicability without further optimization.

Wang et al. [8] proposed a multimodal residual network combined with federated learning to address data privacy and distribution issues in fault detection. By integrating waveform data with environmental features (e.g., weather conditions), the model improves generalization across different regions. Although the approach significantly enhances classification accuracy, it requires large-scale distributed data infrastructure and further expansion of real-world datasets.

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

References	Key Contribution	Limitations
[1]	HSPAN-GNN model with graph convolution, SPD-Conv, and attention mechanisms for improved detection	High computational complexity, redundancy, not suitable for low-resource systems
[2]	Hybrid ML + Generative AI with synthetic dataset (GAN) and autoencoder for unseen fault detection	Limited real-world validation, weak modeling of renewable variability
[3]	LSTM-based prediction integrated with Mho relay for transmission line fault analysis	Based on simulated data, lacks noise robustness evaluation
[4]	LSTM autoencoder for unsupervised anomaly detection with strong noise resilience	Depends on dataset diversity, limited generalization across grid topologies
[6]	DSP (WPT) + DL hybrid framework for accurate fault detection and localization	Real-time deployment and adaptive learning not addressed
[7]	ANN-RF hybrid with SMOTE and Optuna achieving very high accuracy	Computationally expensive, relies on synthetic data
[8]	Federated learning with multimodal residual networks for improved generalization	Requires large-scale distributed infrastructure and real-world datasets

From the above studies, several key gaps emerge:

- Limited integration of DSP-based feature engineering with deep learning models
- Insufficient focus on robustness under noisy measurement conditions
- Heavy reliance on complex architectures (GNN, LSTM, hybrid models) with high computational cost
- Lack of lightweight yet highly accurate models suitable for real-time deployment
- Inadequate evaluation under both clean and noisy environments

Our proposed work directly addresses these gaps by:

- Combining DSP feature extraction (zero-sequence, magnitudes, statistical features) with DL
- Using a lightweight MLP model
- Evaluating performance under both clean and Gaussian noisy conditions
- Achieving high accuracy (~99.7%) with strong robustness

III. METHODOLOGY

A. Dataset Description

To support the development of the proposed DSP-assisted deep learning framework for transmission line fault detection in smart grids, a dataset was collected from an advanced MATLAB/Simulink model of a high-voltage power transmission system, as illustrated in Fig. 1 [9]. The simulated system consists of four 11 kV generators positioned at both ends of the transmission line, where faults were introduced at different locations using a transformer-based setup under both faulted and non-faulted operating conditions. The corresponding three-phase voltage and current signals were recorded, resulting in approximately 12,000 labeled samples for model training and evaluation under clean and noisy environments.

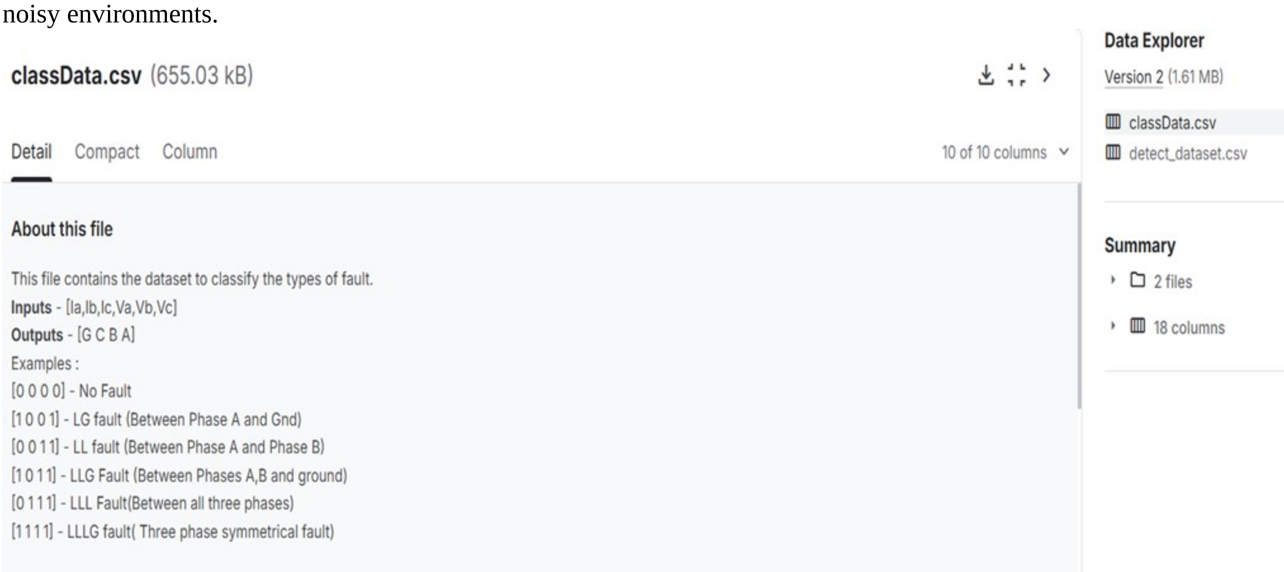


Fig. 1 Dataset of the proposed model

The primary dataset, detect_dataset.csv, contains three-phase current and voltage measurements along with a binary output label indicating fault ('1') or no-fault ('0') conditions. During preprocessing, unnecessary null-value columns were removed to improve data quality. Digital Signal Processing (DSP) techniques were then applied to extract informative features from the electrical signals, which were used as inputs to the proposed Multi-Layer Perceptron (MLP) model for accurate fault detection. Additionally, Gaussian noise was introduced to evaluate the robustness of the proposed framework under realistic noisy smart grid conditions.The auxiliary dataset classData.csv was used for additional analysis and visualization of transmission line fault scenarios. It includes phase-wise indicators and ground involvement information, which help in understanding different fault conditions in the simulated smart grid system.

B. Data Processing

The workflow, conceptually depicted in Fig. 2, started from data collection on the dataset, using detect_dataset.csv for fault detection and classData.csv for fault type analysis. Raw instantaneous current (Ia, Ib, Ic) and voltage (Va, Vb, Vc) measurements were obtained in this first acquisition. The subsequent Data Cleaning & Preprocessing step resolved data quality problems by dropping completely null columns (i.e., df_detect's 'Unnamed: 7' and 'Unnamed: 8') so as to have a strong ground for the analysis. This polished data then advanced to feature engineering, which was an instrumental step in which we utilized a plethora of DSP techniques. Six DSP features, including instantaneous zero-sequence current (I_zero_seq), zero-sequence voltage (V_zero_seq), total instantaneous current magnitude (I_mag_total), total instantaneous voltage magnitude (V_mag_total), maximum absolute value of instantaneous current (I_max_inst), and maximum absolute value of instantaneous voltage (V_max_inst), were extracted from the raw signals of both df_detect and df_class in order to increase their discrimination power. After feature extraction, the df_detect dataset was passed for data splitting into training (70%), validation (15%), and test (15%) stratified sets, and its features were normalized with StandardScaler to normalize their ranges. In the Model Training step, we developed an MLP (multiple-layer perceptron) deep learning model with TensorFlow/Keras comprising Dense layers followed by ReLU activation and

Dropout regularization, which was then optimized with the Adam optimizer and binary_crossentropy loss. The model was trained over 50 epochs with a batch size of 32 using the original scaled data and its noisy counterpart (with added Gaussian noise, mean=0, std=0.1). In model evaluation, the performance of the model was found to be excellent on clean test data; it has obtained an accuracy score of 0.9972 with 5 misclassifications (3 false positives and 2 false negatives) in a total of 1801 samples. Importantly, if we retrain with a noisy test dataset and evaluate, the model maintains reasonable robustness and achieves an accuracy of 0.9922 with a small increase to 14 misclassifications (5 false positives, 9 false negatives), indicating it is still very robust. The process should ultimately lead to model deployment for practical use in the real world, or it can cycle back going through more refining according to the results of evaluation.

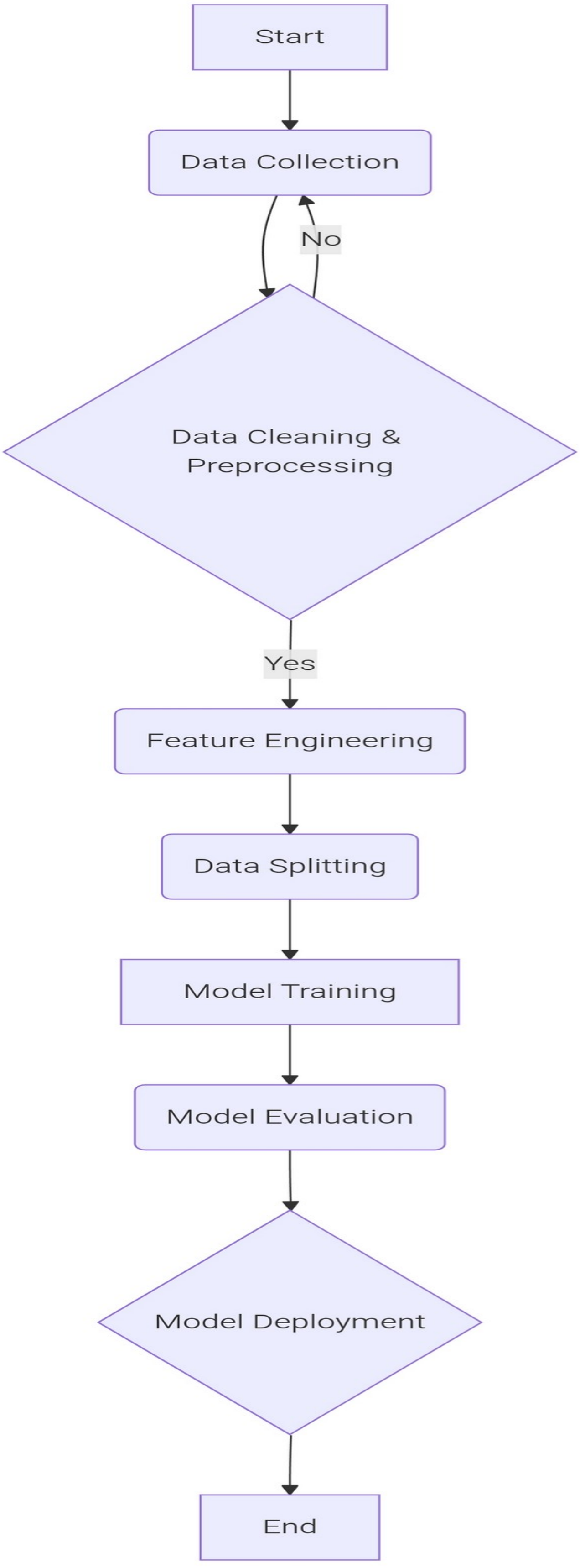


Fig. 2 Data Processing

C. Digital Signal Processing (DSP) Techniques Used on The Model

An essential role was played by the DSP techniques, which transformed the raw inductor current and voltage measurements into a discriminative feature set for fault detection. In particular, for the detect_dataset dataframe, six key features were carefully computed from the three-phase voltage and current signals to enhance the binary classification performance (fault vs. no-fault) of the proposed model.

Instantaneous Zero-Sequence Current (I_zero_seq): It is computed by adding instantaneous phase currents (Ia + Ib + Ic). This function is highly sensitive to earth faults.

Instant Zero-Sequence Voltage (V_zero_seq): Defined as the sum of the instantaneous three-phase voltages (Va + Vb + Vc). Just like current, this aids in sensing a ground fault.

Total Current Magnitude (I_mag_total): Calculated as the Euclidean norm of the phase currents ($I_{mag_{total}} = \sqrt{I_a^2 + I_b^2 + I_c^2}$). This is an aggregated status of current conditions.

Total Instantaneous Voltage Magnitude (V_mag_total): Calculated as the Euclidean norm of the three-phase voltages ($V_{mag_{total}} = \sqrt{V_a^2 + V_b^2 + V_c^2}$). This provides a single indication of voltage error.

Maximum Instantaneous Absolute Current (I_max_inst): Maximum absolute value of the phase currents at each instance (¿). This highlights peak current excursions.

Maximum Instantaneous Modulus Voltage (V_max_inst): The greatest absolute value among the instantaneous phase voltages (¿). This indicates peak voltage deviations.

These DSP-based features successfully converted the raw time-series data into a compact and physically interpretable form, considerably enhancing feature space for further deep learning tasks by emphasizing key fault occurrence and type information.

D. Applied Gaussian Noise on The Model

To evaluate the robustness and generalization performance of the proposed deep learning framework in real-world operating environments where sensor readings are frequently affected by noise, we applied an augmentation. That is, Gaussian noise was added to the preprocessed feature sets. This noise was added with a zero mean and a standard deviation of 0.1, which were selected to model the average measurement errors and random fluctuations that may take place in smart grid systems. This noise was acted element-wise on the scaled training, validation, and test datasets (X_train_scaled, X_val_scaled, X_test_scaled) to obtain three augmented datasets: namely, X_train_noisy, X_val_noisy, and the noisy version of test (respectively, X_test_noisy). Also, to directly demonstrate the noise effect on the DSPs-based features, Ia, Ib, Ic, Va, Vb, and Vc raw current and voltage columns in df_class The DataFrame was corrupted by applying the same Gaussian noise parameters; then we re-calculated the DSPs features to generate df_class_noisy. This controlled introduction of noise provided the opportunity to examine the robustness and feasibility of this model under intolerable conditions.

1.The Gaussian (Normal) Distribution Equation:

This defines the distribution $N(\mu, \sigma^2)$ from which the noise was sampled, where $\mu = 0 \wedge \sigma = 0.1$.

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

2. The Additive Noise Transformation:

$$X_{noisy} = X_{scaled} + \epsilon, where\, \epsilon \sim N(\mu, \sigma^2)$$

3. Application to Phase Currents/Voltages

$$I_{a,noisy} = I_a + N(0, 0.01)$$
$$where\ 0.01\ is\ \sigma^2\ when\ \sigma = 0.1$$

E. Architecture of The Model Without Gaussian Noise

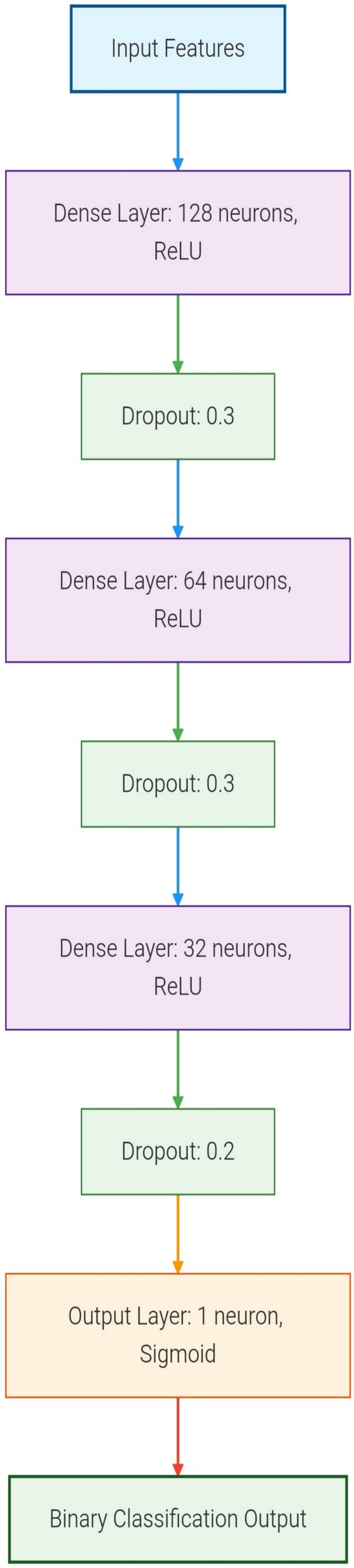


Fig. 3 Architecture of The Model Without Gaussian Noise

The deep learning model shown in Fig. 3 is built as an MLP for binary classification. It receives the pre-processed features and passes them to a number of dense layers with ReLU activation. Namely, the architecture consists of three hidden dense layers with 128, 64, and 32 neurons. To avoid overfitting, a dropout layer is added after every hidden layer with rates of 0.3, 0.3, and 0.2, respectively. The last layer is only one dense neuron with a sigmoid activation function, resulting in a probability output for binary failure detection.

F. Architecture of The Model With Gaussian Noise

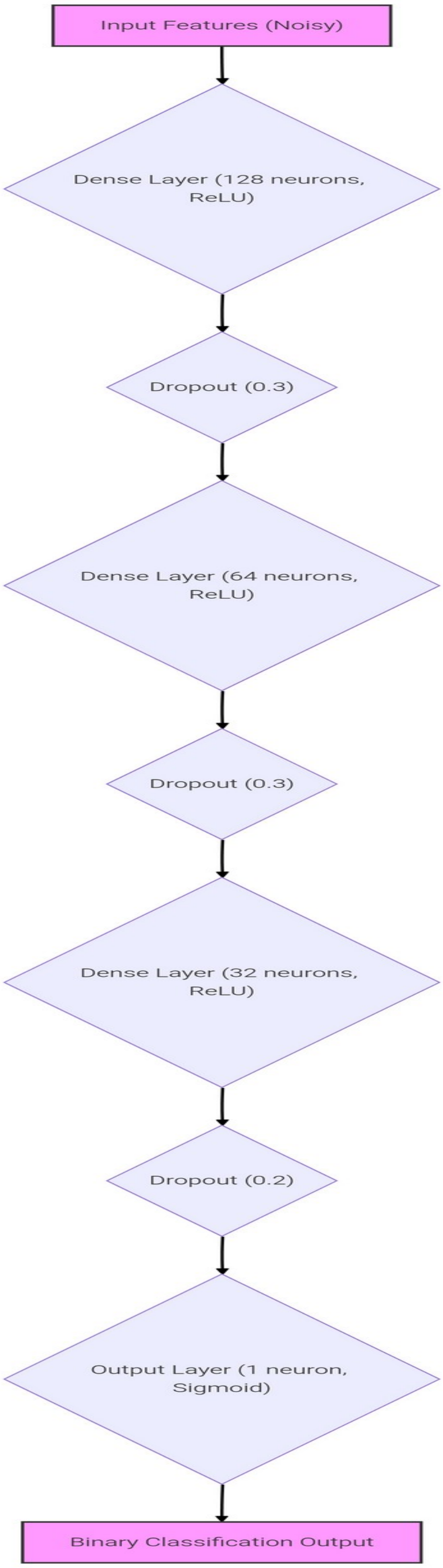


Fig. 4 Architecture of The Model With Gaussian Noise

The deep learning model used for fault diagnosis, especially under noisy conditions, is based on curve designs of sequential multilayer perceptrons (MLPs) presented in Fig. 4. The procedure begins with the input features (in this case, DSP-extracted measurements obtained from smart grid current and voltage signals)—a priori noisy observations artificially added with Gaussian noise to mimic real measurement uncertainties. These noisy inputs are then passed through the first dense hidden layer that contains 128 neurons and uses ReLU activation to capture some basic non-linear relationships in the perturbed data. In order to limit overfitting and also make the model more robust to noise, a dropout layer with a 0.3 rate is added after the first dense layer. This regularization method stochastically drops out a portion of the neurons during learning, which enforces the network to learn robust and dispersed feature representations. Then, the data goes through a second dense layer of 64 neurons with ReLU activation, followed by another dropout layer where we discard 30% of the information to improve the feature generalization. A third dense layer follows with 32 neurons and ReLU activation, and also before output, a final dropout with a rate of 0.2. The architecture is topped by a single-neuron output layer activated with the sigmoid function that outputs the probability score for binary classification (fault or no-fault event). This architecture, and in particular the inclusion of dropout layers, allows the model to process corrupted input features and still classify them adequately while keeping good performances even under noisy conditions.

IV. RESULTS WITHOUT GAUSSIAN NOISE

A. Training and Validation Performance Without Gaussian Noise

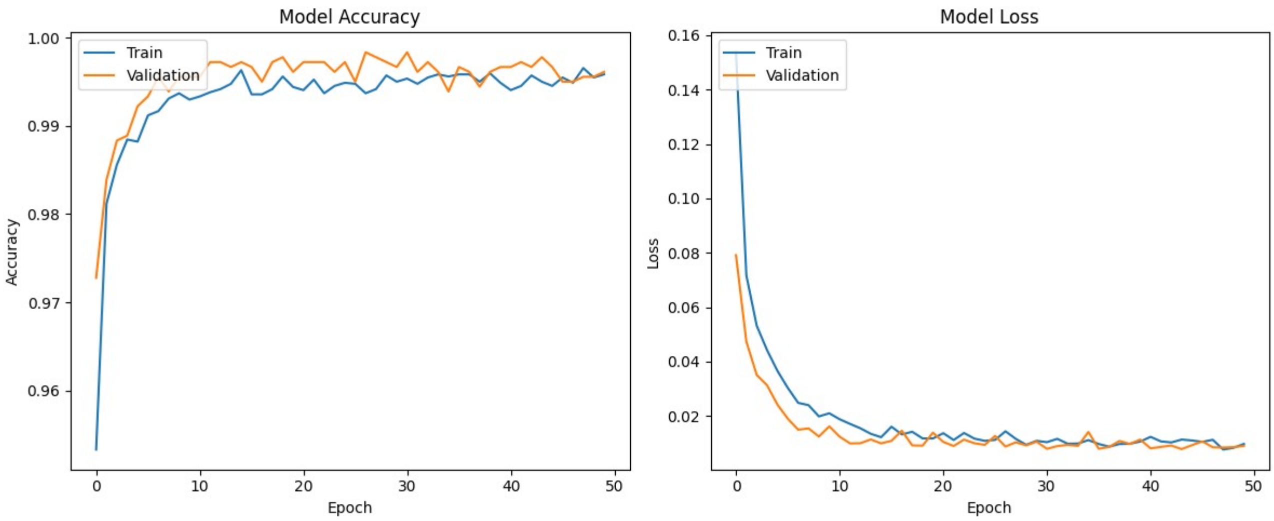


Fig. 5 Training and Validation Accuracy and Loss Curves Without Gaussian Noise

The learning curves shown in Fig. 5 of the deep model trained on clean data show good and steady convergence. Training accuracy was always going up at nearly optimal rates, and validation accuracy tightly followed that, making good values also. This proximity of training and validation accuracies shows very good generalization ability, with little overfitting. Meanwhile, both the training and validation loss followed a descending tendency across the epochs in an even manner, eventually tending to be around the lowest point. The fast convergence of these curves can be interpreted as tight training, where the model learned rapidly the intrinsic patterns of clean DSP-extracted features. Such a strong result on clean data is informative regarding an upper bound of how effective the model can be in ideal settings.

B. Confusion Matrix and Classification Report

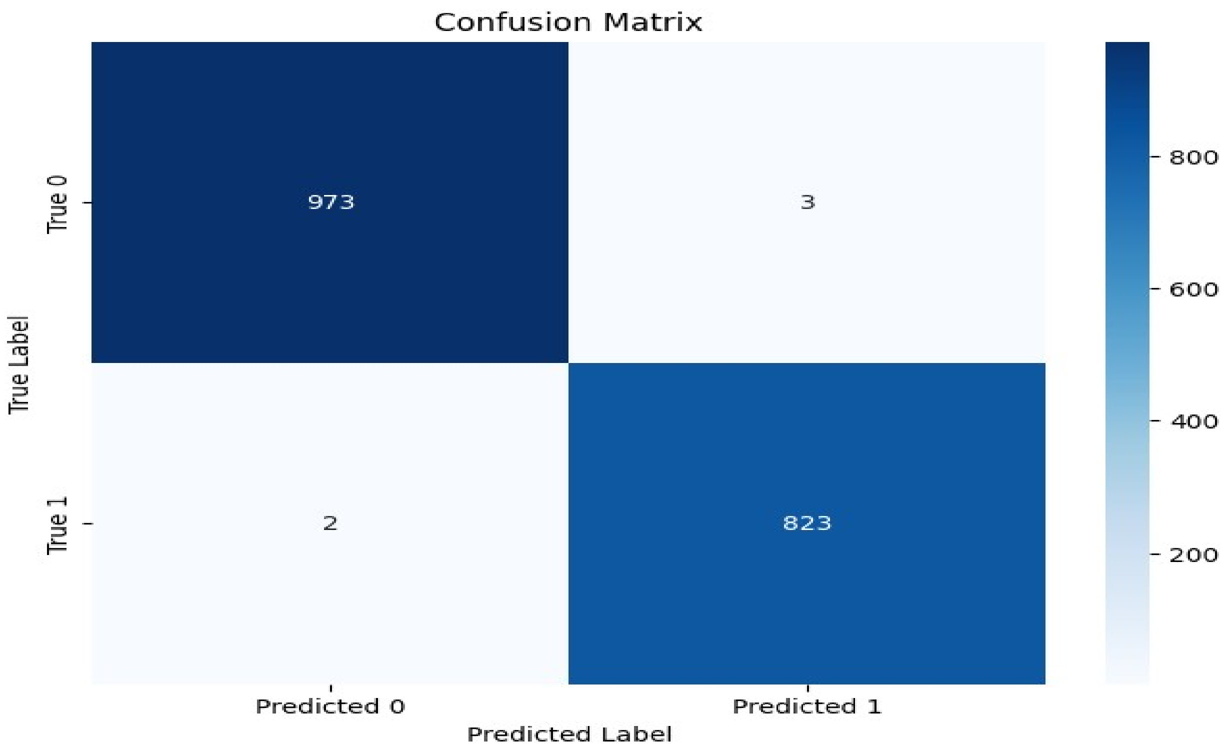


Fig. 6 Confusion Matrix

Confusion Matrix:

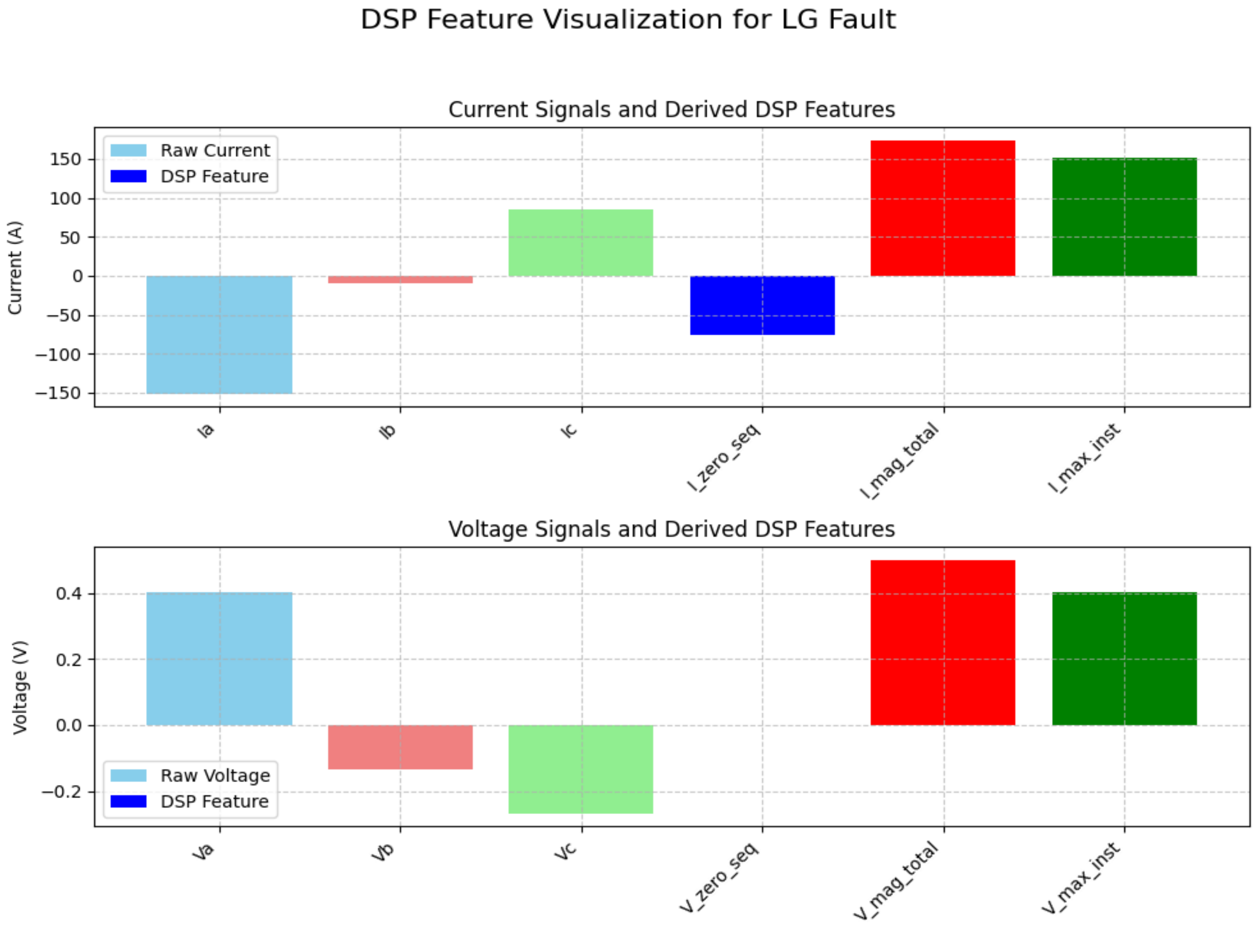
[[973 3]
[2 823]]

Table 2 presents the classification report for the clean dataset, demonstrating the strong performance of the proposed model for fault detection. For both classes—0 (No Fault) and 1 (Fault)—the model achieves precision, recall, and F1-score values of 1.00, indicating highly accurate and balanced classification performance. The support values show that the test dataset consists of 976 No-Fault and 825 Fault samples. Further analysis of the confusion matrix in Fig. 6 confirms the robustness of the model, where 973 true negatives and 823 true positives are correctly classified out of 1801 test samples. Only 3 false positives and 2 false negatives are observed, reflecting a very low misclassification rate. These results clearly demonstrate the effectiveness of the proposed framework in accurately distinguishing between fault and no-fault conditions, which is critical for ensuring the reliability and stability of smart grid transmission systems.

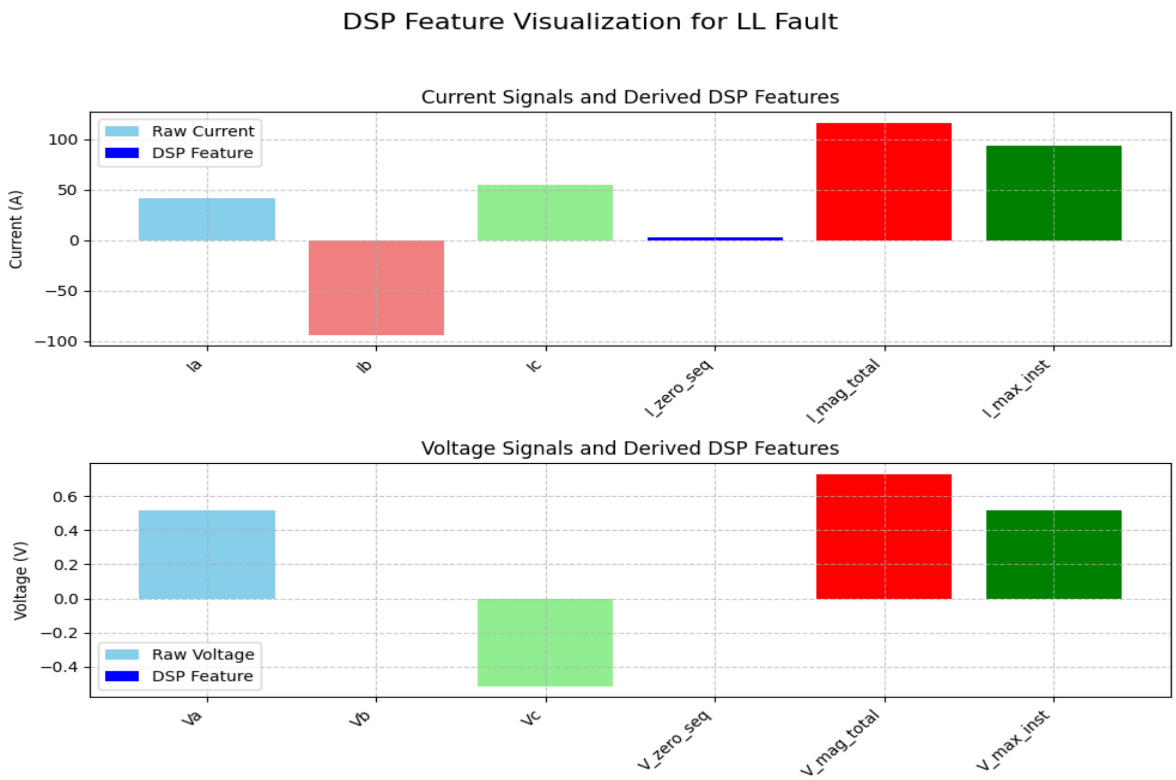
TABLE 2. Classification Report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	976
1	1.00	1.00	1.00	825
accuracy			1.00	1801
macro avg	1.00	1.00	1.00	1801
weighted avg	1.00	1.00	1.00	1801

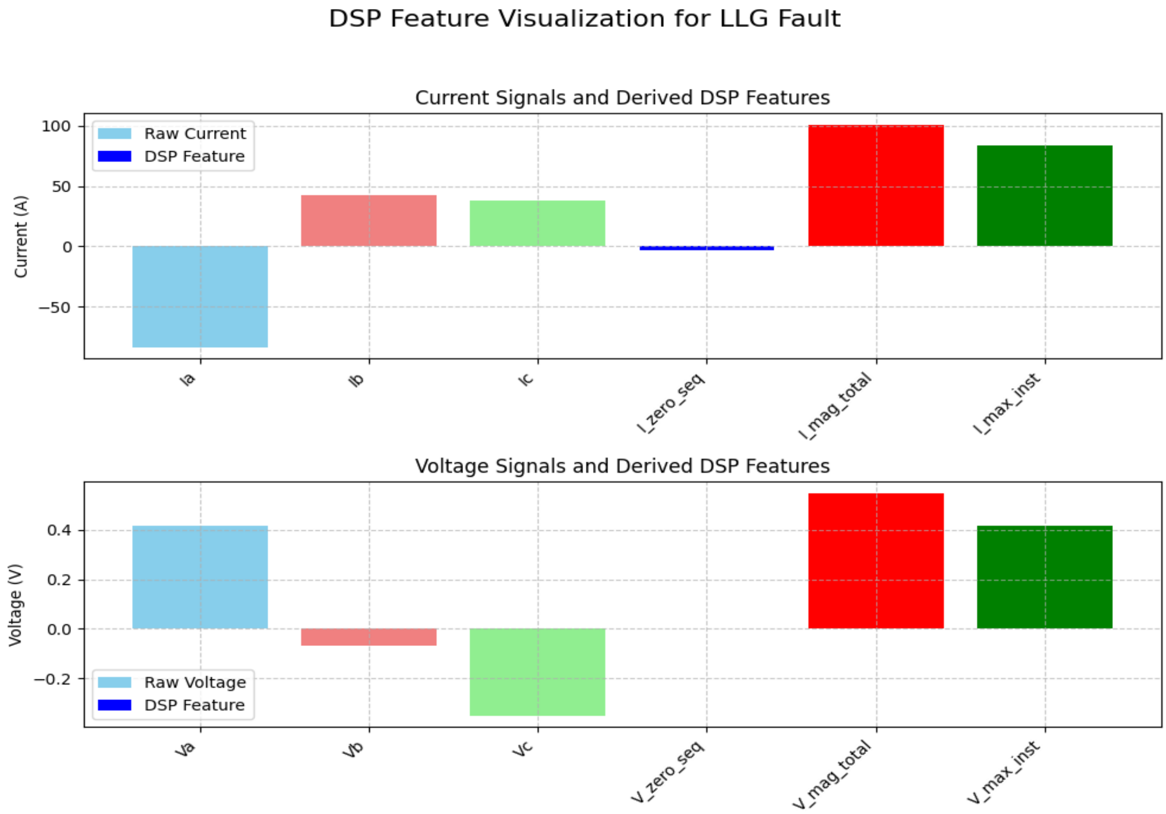
C. Visualizations of Raw Signals and DSP Features for Representative Fault Types



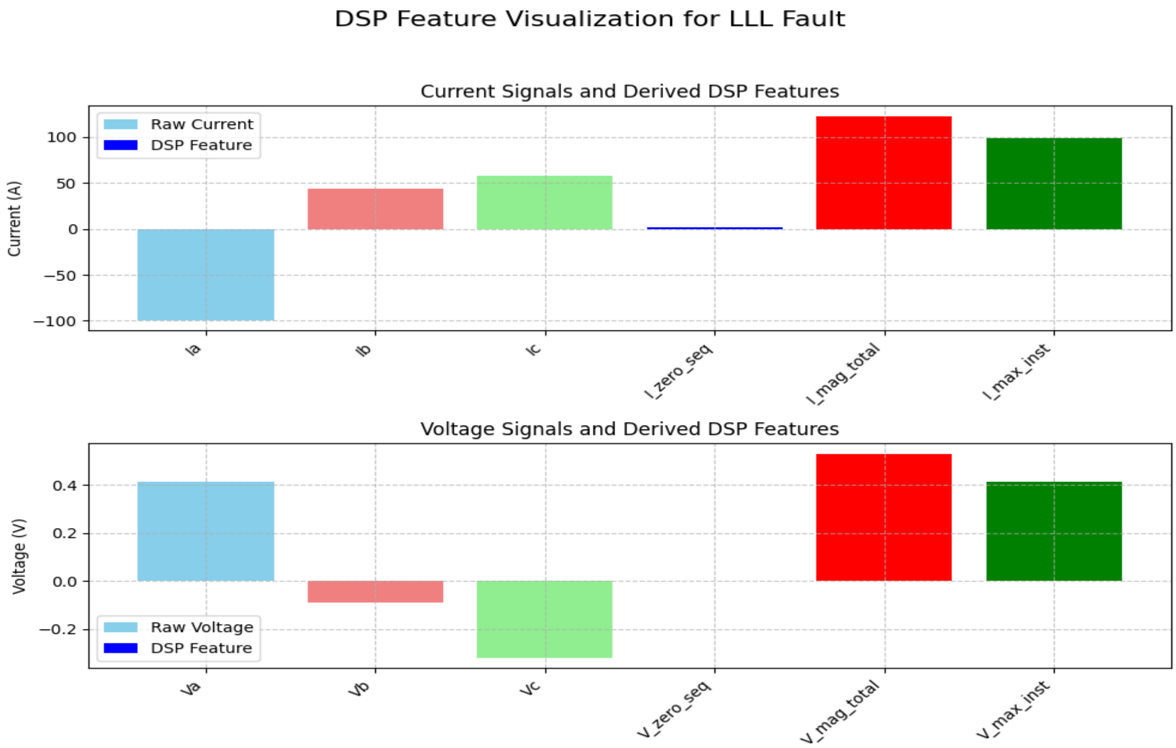
(a) DSP Features Visualization for LG Fault



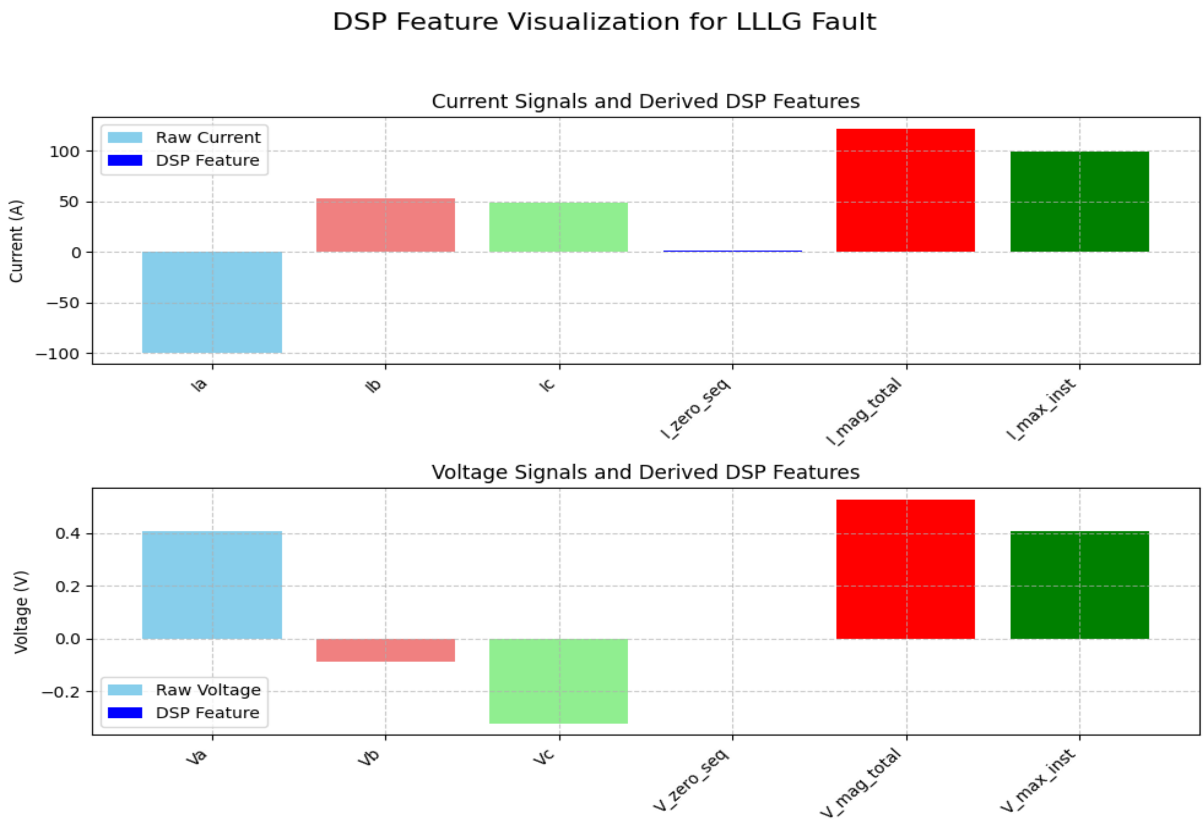
(b) DSP Features Visualization for LL Fault



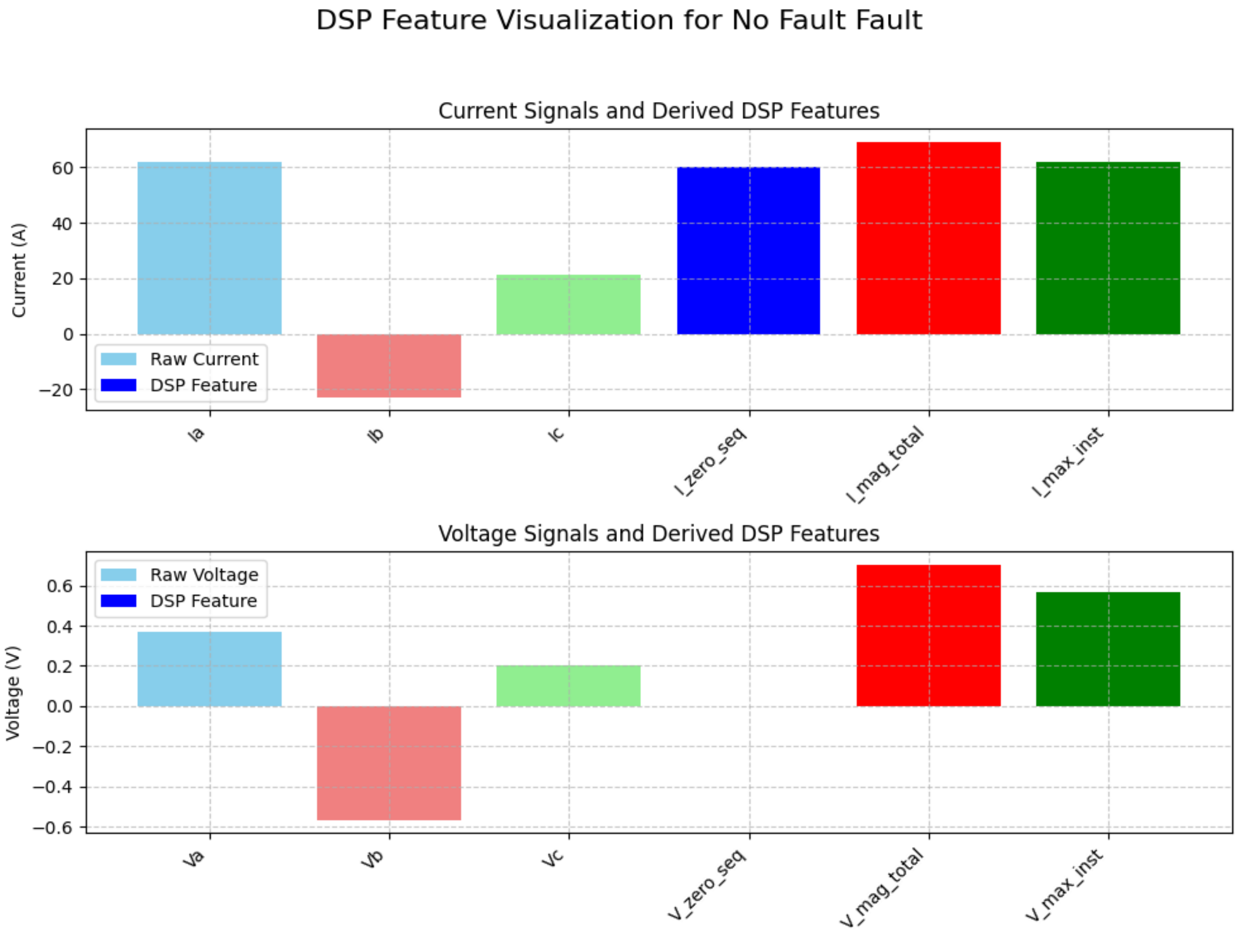
(c) DSP Features Visualization for LLG Fault



(d) DSP Features Visualization for LLL Fault



(e) DSP Features Visualization for LLLG Fault



(f) DSP Features Visualization for No Fault

Fig. 7 Visualizations of Raw Signals and DSP Features for Representative Fault Types

The visualizations of raw signals and DSP-extracted features from the clean dataset provide important insights into the effectiveness of the feature engineering process for fault detection. The bar graphs presented in Fig. 7 illustrate how raw instantaneous three-phase current and voltage measurements (Ia, Ib, Ic and Va, Vb, Vc) are transformed into a compact and informative feature set to enable reliable binary classification (fault vs. no-fault). While raw signals exhibit complex oscillations that may conceal subtle fault-induced anomalies, the DSP-derived features reveal these hidden characteristics in a more distinct and amplified form. In particular, features such as I_zero_seq and V_zero_seq highlight the presence of current and voltage imbalance, which remain near zero under normal conditions but increase significantly during fault events, thereby serving as strong indicators of system disturbance. Similarly, I_mag_total and V_mag_total capture the overall magnitude variations during abnormal conditions, while I_max_inst and V_max_inst reflect transient peak behaviors associated with faults. Collectively, these DSP-based representations effectively transform raw electrical measurements into discriminative features, providing a strong foundation for accurate transmission line fault detection using the proposed deep learning model.

D. Visualizations of DSP Features for Specific Fault Types

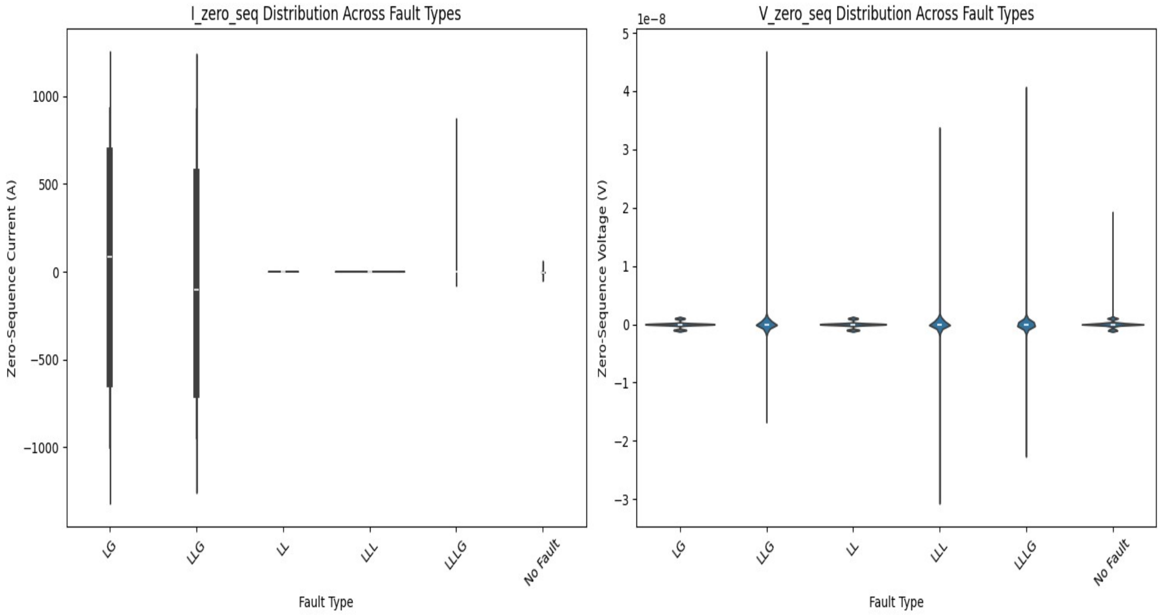


Fig. 8 Visualizations of DSP Features for Specific Fault Types

Violin plots shown in Fig. 8 compare the discriminative power between I_zero_seq and V_zero_seq for fault types. Moreover, the characteristic patterns between ‘no fault' and fault directions ('LG', ‘LLG’, etc.) were analyzed, suggesting that zero sequence components can be used as effective indexes of different fault states. These pictures confirm the empirical interpretation of features and strong connection with type of fault.

V. Results With Gaussian Noise

A. Training and Validation Curve of the Model With Gaussian Noise

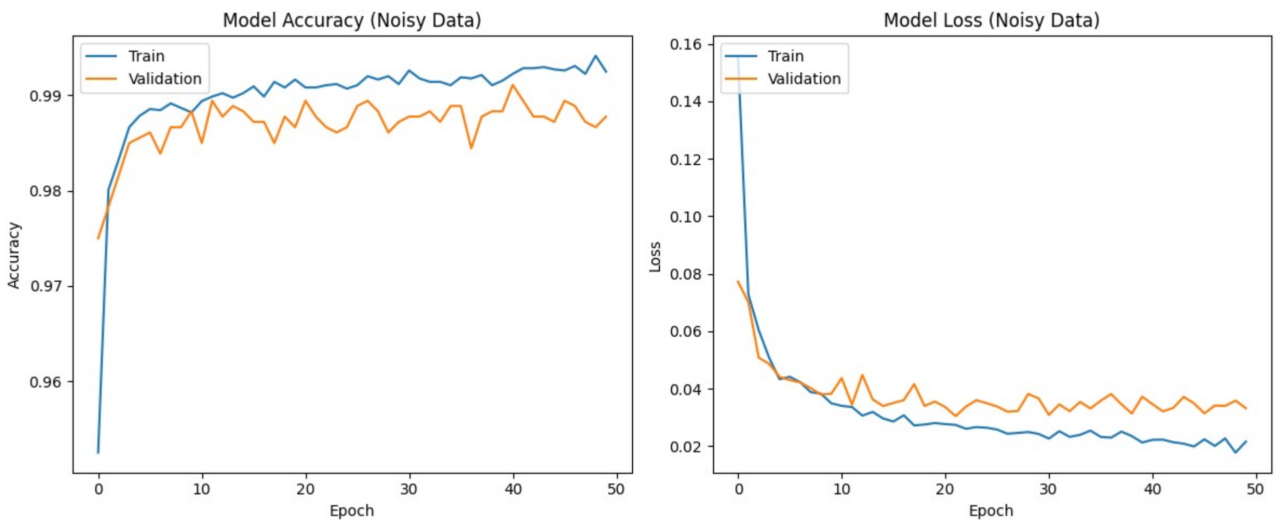


Fig. 9 Training and Validation Curve of the Model With Gaussian Noise

The learning curves of such a retrained deep learning model with noise (mean=0, std=0.1) give a number of important indications about its performance and robustness. Fig. 9 confirms that both the training accuracy and validation accuracy increase monotonically across epochs, which means the model is capable of learning patterns from distorted input effectively. Both the training loss and validation loss are decreasing at a slow rate, which indicates that the model is capable of reducing errors on both seen and unseen data with noises.

The noisy data trends are slightly noisier than the clean-trained curves, particularly in the validation loss when compared to that of a model trained on standard data. This is expected due to the stochastic nature of noise, because of the residual unpredictability brought about by stochastic noise. Regardless of these oscillations, the validation accuracy stays impressively close to the training accuracy, and both tend to high values, which hints that the model is robust and generalizes well on noisy data not really seen while it doesn't overfit. This shows that the framework is robust against measurement uncertainties in practice, which can be found in a smart grid environment.

B. Classification Report and Confusion Matrix for Noisy Data

TABLE 3. Classification Report (Noisy Data)

	precision	recall	f1-score	support
0	0.99	0.99	0.99	976
1	0.99	0.99	0.99	825
accuracy			0.99	1801
macro avg	0.99	0.99	0.99	1801
weighted avg	0.99	0.99	0.99	1801

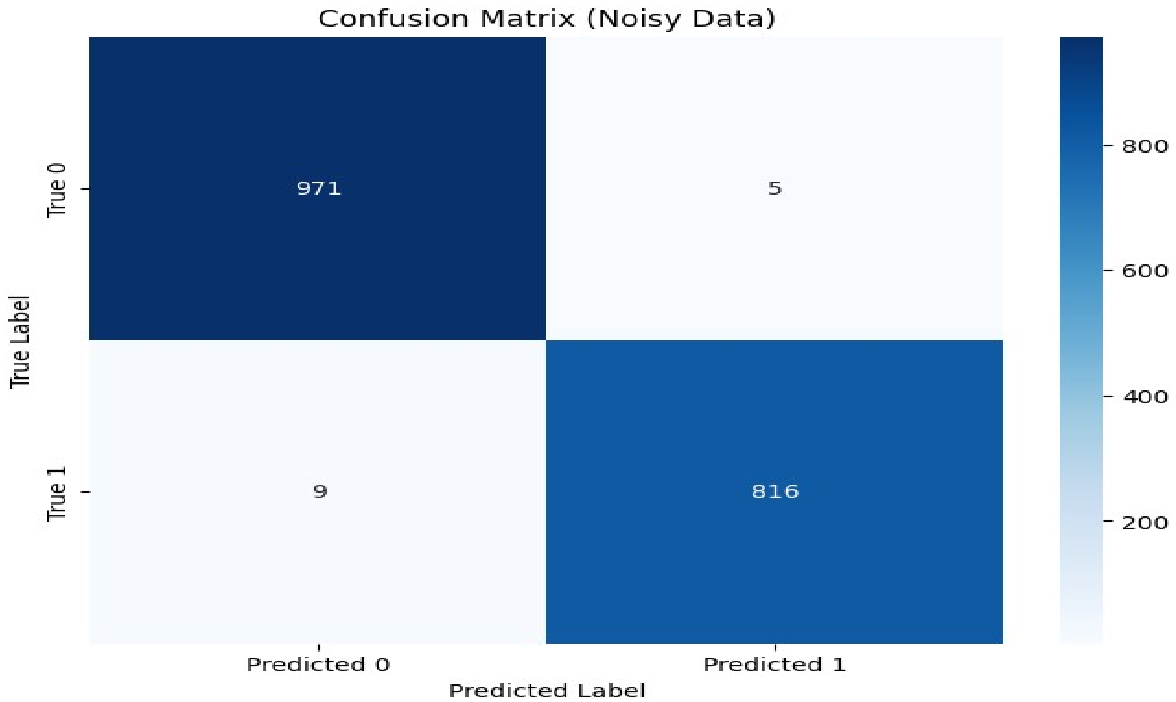


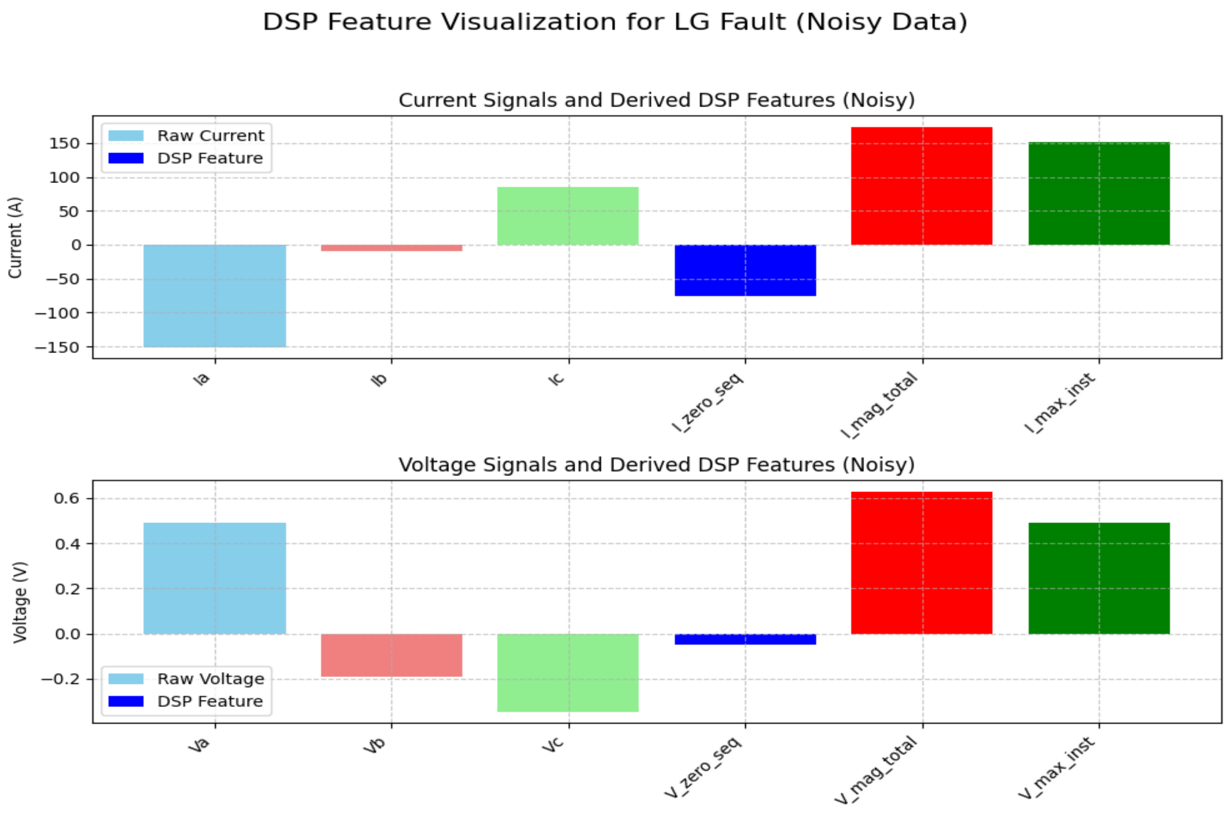
Fig. 10 Confusion Matrix for Noisy Data

Confusion Matrix (Noisy Data):

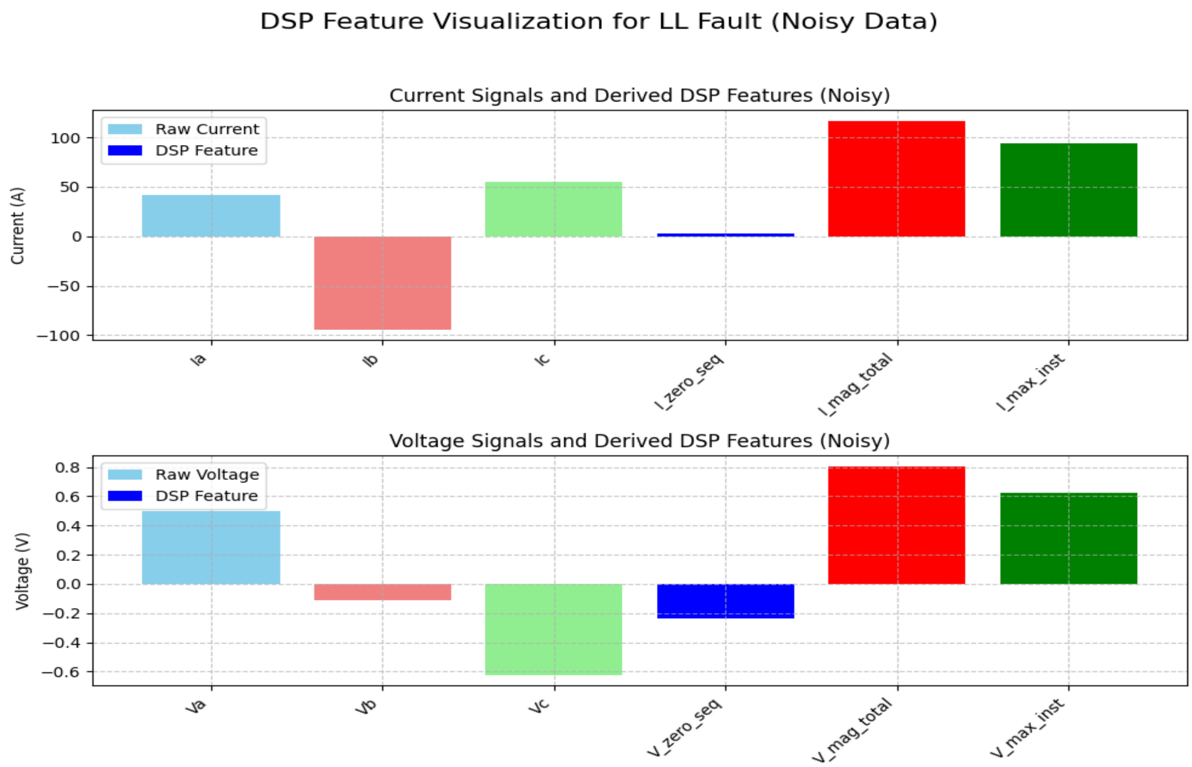
[[971 5]
[9 816]]

The deep learning model was also retrained on the datasets augmented with Gaussian noise (mean=0, standard deviation=0.1) to evaluate whether it was not only insensitive to such outlook. The retrained model kept the high accuracy with a test loss of 0.5185 and a test accuracy of 0.9922 on the noisy test dataset. The Classification Report for the noisy data model is represented in Table 3. The confusion matrix of the noisy data model is illustrated in Fig. 10. In comparison with the clean data model, 5 false positives and 9 false negatives were observed in the noisy data model. Although the performance was a little worse than in clean data, the model correctly identified 971 true negatives and 816 true positives. This demonstrates that the noise level is resistant to a high level of abuse.

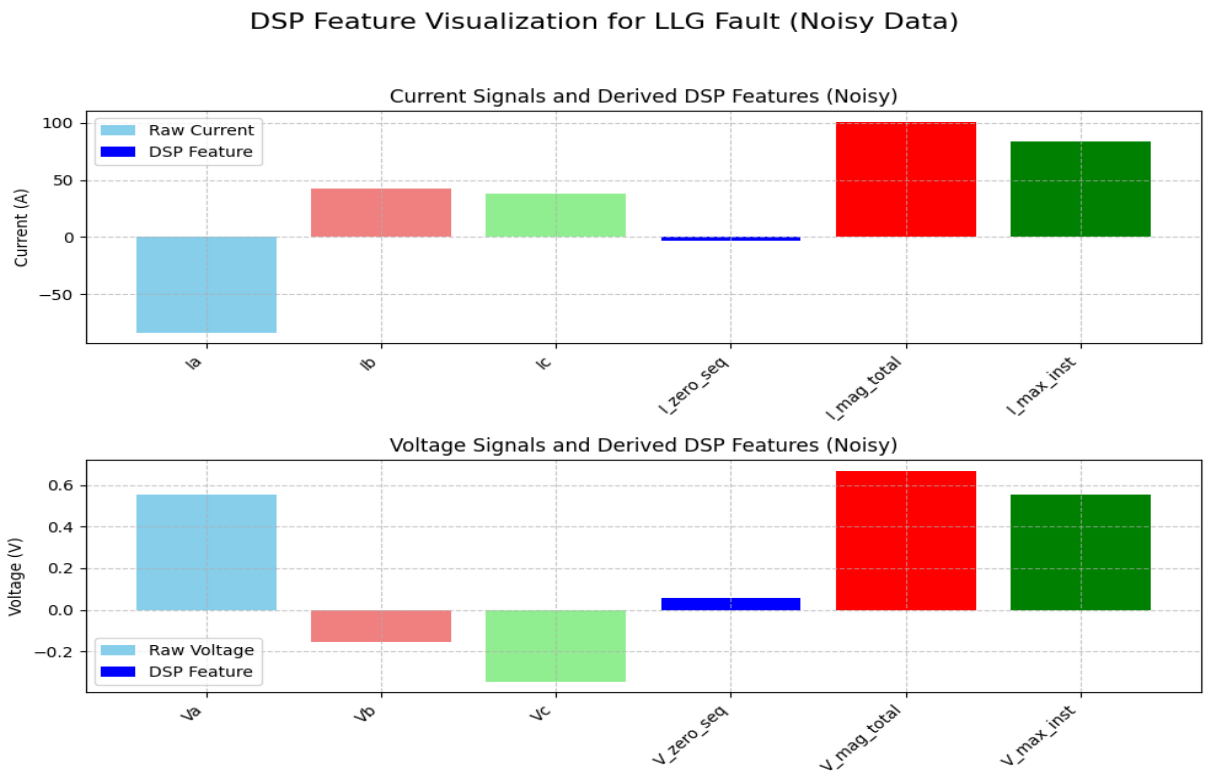
C. Visualizations of Noisy Raw Signals and noisy DSP Features for Representative Fault Types



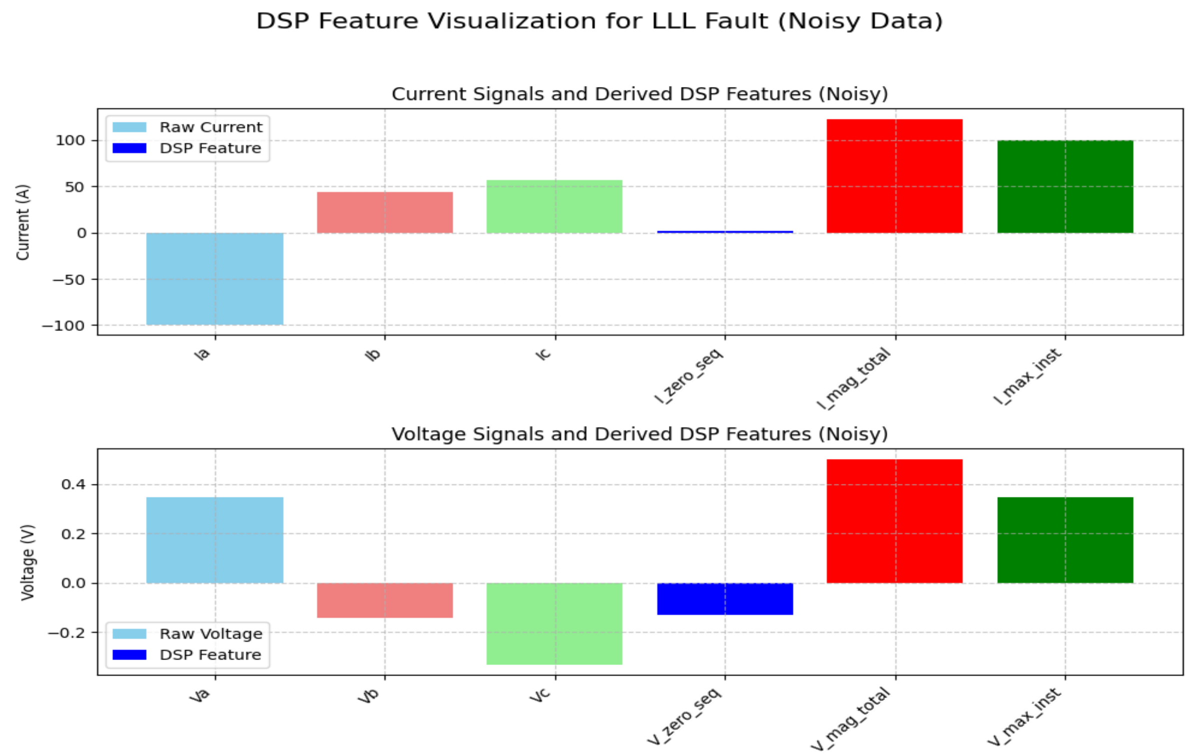
(a) DSP Features Visualization for LG Fault (Noisy Data)



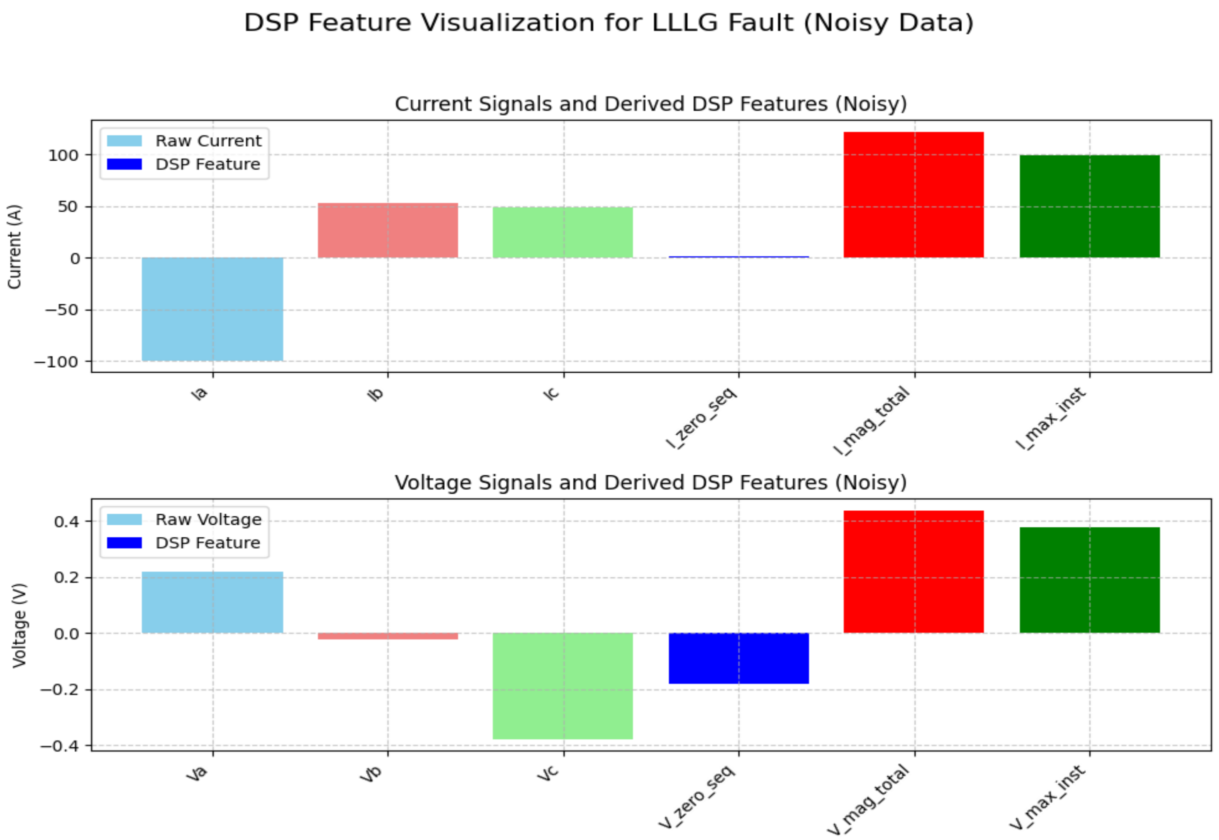
(b) DSP Features Visualization for LL Fault (Noisy Data)



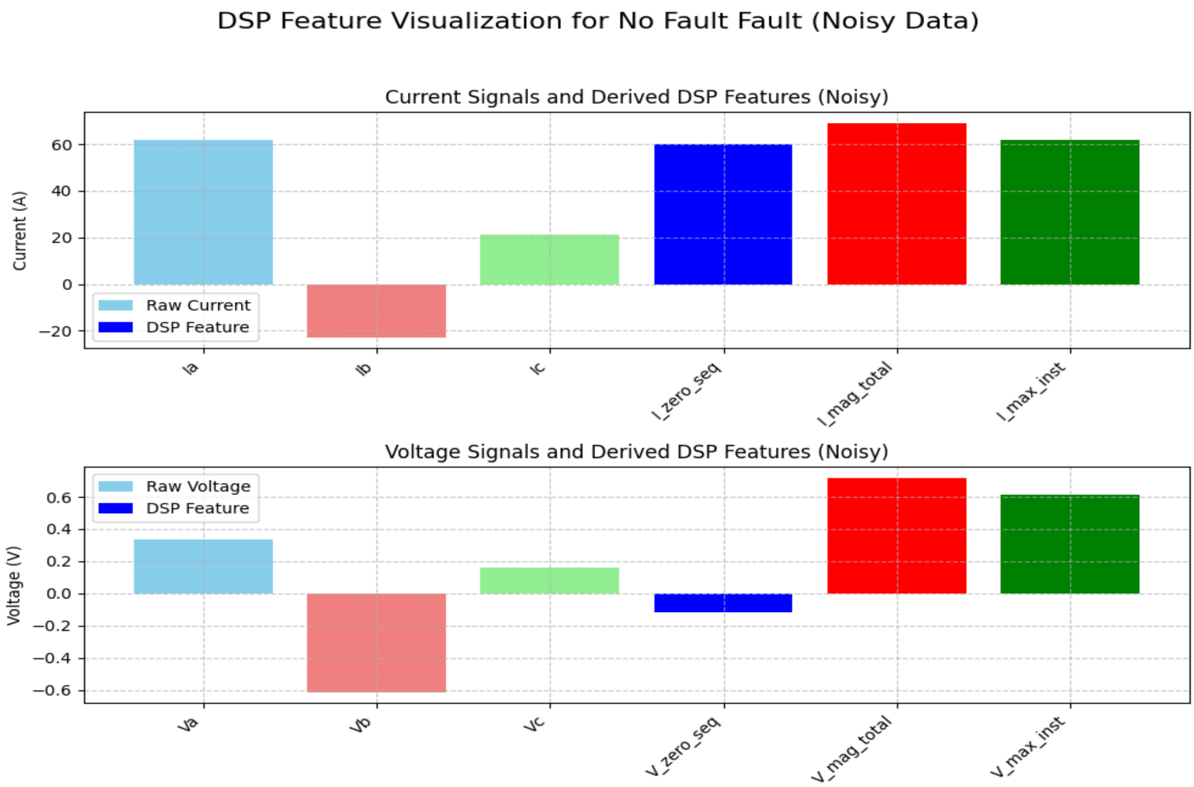
(c) DSP Features Visualization for LLG Fault (Noisy Data)



(d) DSP Features Visualization for LLL Fault (Noisy Data)



(e) DSP Features Visualization for LLLG Fault (Noisy Data)



(f) DSP Features Visualization for No Fault (Noisy Data)

Fig. 11 Visualizations of Noisy Raw Signals and noisy DSP Features for Representative Fault Types

The visualizations shown in Fig. 11 of noisy raw signals and corresponding DSP with added Gaussian noise give direct implications on how the Gaussian noise affects the data. These results demonstrate the influence of introduced Gaussian noise (mean = 0, standard deviation = 0.1) on raw current and voltage signals for different fault types. Each bar graph represents a sample representative of one type of fault, namely 'No Fault,' 'LG,' 'LL,' 'LLG,' 'LLL,' and 'LLLG.' Firstly, the raw figures of currents and voltages (Ia, Ib, Ic, Va, Vb, and Vc) show larger variance and more wavy patterns as a result of additional Gaussian noise added into the original measurements themselves, which visually presents that the disturbance on data is successful. However, even with this uncertainty in the raw signals, it can be observed that there remains substantial discrimination capability in the recalculated DSP features (I_zero_seq, V_zero_seq, I_mag_total, V_mag_total, I_max_inst, and V_max_inst). Although they are impacted by the noise, their values and interrelations related to fault goings-on generally remain as well. For example, the magnitudes of zero-sequence components (I_zero_seq, V_zero_seq) are consistently greater during noisy fault conditions relative to noisy no-fault conditions, which indicates that the underlying physical characteristics presumed by these DSP features tend not to be corrupted excessively by some noise in fact. They are also essential for illustrating that in debasing noise conditions anyway, these designed DSP characteristics still carry useful insights for the indication of faults, which is supported by the quantitative results from a model trained on noisy data and demonstrates the robustness of the feature extraction approach without reliance on perfect measurements.

D.Visualizations of Noisy DSP Features Distributions for Specific Fault Types

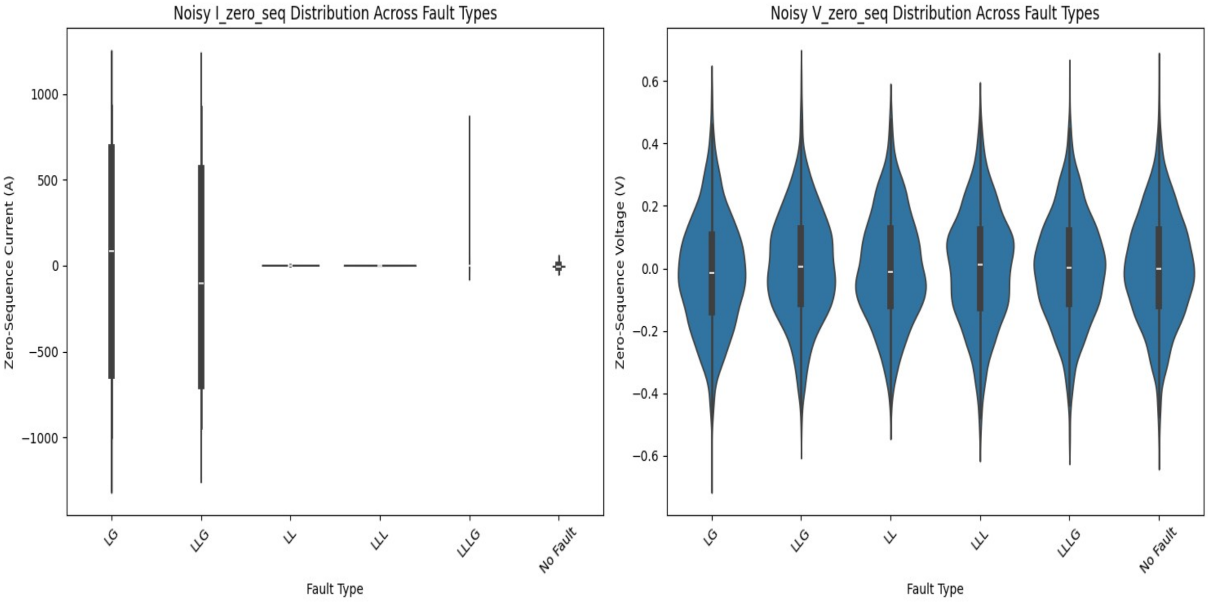


Fig. 12 Visualizations of Noisy DSP Features Distributions for Specific Fault Types

The violin plot in Fig. 12 describing the statistical distribution of I_zero_seq noisy and V_zero_seq per each fault type provides significant information about the robustness of digital signal processing (DSP) characteristics under simulated measurement error. As can be seen from these visualizations, adding Gaussian noise with standard deviation equal to 0.1 results in significantly wider distributions for all fault types, compared to the corresponding clean data. This greater spread is the natural result of some random variations about the points being injected, resulting in a wider spread in each (the cut-off distributions are presumably no longer sharp enough for clear violin shape). Nevertheless, a key observation is that the basic discrimination patterns among different classes of fault are well preserved. For example, the plots for I_zero_seq still present a good splitting of "No Fault" data (data points remain densely packed around zero) and different fault types with strong variations. In the same way, the characteristic distributions of V_zero_seq are preserved and can be exploited perfectly to distinguish different fault conditions. This continued capability of the DSP features to disclose system asymmetry, also in the presence of noise, highlights their inherent robustness and ability to keep physically meaningful properties of a failure condition. This robustness of the proposed network is an important aspect in practical smart grid implementations, as the real-world sensor data is often noisy, confirming that a state-of-the-art deep model trained using such noise-augmented data can perform accurately and consistently accurate fault localization.

E. Model Performance Comparison: Clean vs. Noisy Data

TABLE 4. Model Performance Comparison: Clean vs Noisy Data

Metric	Clean Data Model	Noisy Data Model
Overall Metrics		
Test Loss	650.8352	0.5185
Test Accuracy	0.9972	0.9922
Confusion Matrix (Counts)		
True Negatives (Class 0)	973	971
False Positives (Class 0 as 1)	3	5
False Negatives (Class 1 as 0)	2	9
True Positives (Class 1)	823	816

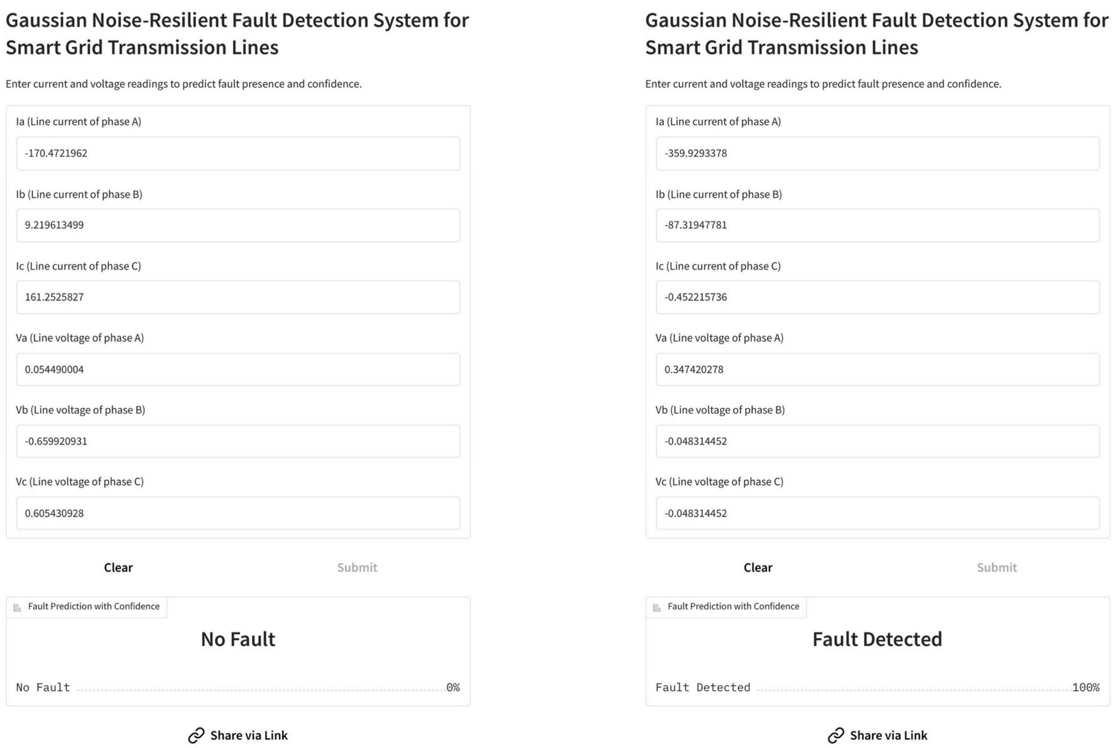
This bare comparison in Table 4 indicates the robustness of the proposed deep learning method. The model obtained a high test accuracy of 0.9972 on clean data and made very few misdiagnoses (3 false positives and 2 false negatives). When adding Gaussian noise (mean=0, std=0.1) and retraining with clean samples only, the model performance is still quite good: test accuracy is 0.9922. Although there is a little drop in accuracy and an increase of false positives (from 3 to 5) and false negatives (from 2 to 9), this small loss on noisy data, only about 0.5 percentage points, shows that the model is robust. That it could retain even such high performance under severely perturbed conditions also suggests that the DSP-extracted features and deep learning architecture are effective in dealing with real sensor imperfections.

TABLE 5. Comparative Analysis of the Proposed Model and Recent State-of-the-Art Methods

Study	**Research topic**	**Model**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 score (%)**
[1]	Fault Detection	HSPAN-GNN	92.11	92	90.59	—
[4]	Fault Detection and Localization	LSTM-AE	98	99	99	98
[10]	Fault Diagnosis and Classification	XGBoost+RFE+Domain Knowledge	94.25	94.87	94.57	94.72
[11]	Fault Detection and Classification	CNN-Transformer	97	—	—	—
Proposed Model	Fault Detection	MLP	Clean Data: 99.72 ; Noisy Data: 99.22	Clean Data: 100 ; Noisy Data: 99	Clean Data: 100 ; Noisy Data: 99	Clean Data: 100 ; Noisy Data: 99

Table 5 compares the proposed MLP-based fault detection model with several recent state-of-the-art methods. The proposed model achieved the highest accuracy of 99.72% on clean data and maintained strong robustness under noisy conditions with 99.22% accuracy. It also obtained perfect precision, recall, and F1-score (100%) on clean data, while retaining high values of 99% for all metrics on noisy data. Compared with existing approaches such as HSPAN-GNN, LSTM-AE, XGBoost+RFE+Domain Knowledge, and CNN-Transformer, the proposed method demonstrates superior and more stable performance for transmission line fault detection.

F. Deployment Analysis of the Proposed MLP Model



(a) No Fault Detection (b) Fault Detection

Fig. 13 Deployment of the Proposed DSP-Assisted MLP Model

Figure 13 illustrates the deployment results of the proposed DSP-assisted MLP-based fault detection system for smart grid transmission lines. In Figure 13(a), the deployed model predicts a normal operating condition as “No Fault” with nearly 0% fault probability, while Figure 13(b) shows successful fault detection with 100% confidence due to abnormal current and voltage signal patterns. These results demonstrate the effectiveness of the deployed MLP model in accurately distinguishing between healthy and faulty transmission line conditions under both clean and noisy environments.

VI. CONCLUSION

This paper successfully presented a robust deep learning-based fault detection system for smart grid transmission lines, integrating Digital Signal Processing (DSP) techniques for enhanced feature extraction. The research demonstrated that combining DSP-engineered features, such as zero-sequence components and instantaneous magnitudes, with a multi-layer perceptron (MLP) deep learning architecture yields highly accurate and reliable fault detection capabilities. The model achieved an exceptional accuracy of 99.72% on clean test data, with near-perfect precision, recall, and F1-scores, indicating its strong ability to discern between fault and no-fault conditions.A critical contribution of this study is the comprehensive assessment of the system's resilience to real-world operational noise. By augmenting the dataset with Gaussian noise (mean=0, std=0.1) and retraining the model, the framework maintained remarkable performance, achieving a test accuracy of 99.22% on noisy data. This demonstrates the inherent robustness of the proposed approach and its potential for reliable deployment in environments with imperfect sensor measurements. The DSP features proved effective in preserving critical fault characteristics even amidst noise, enabling the deep learning model to generalize effectively.

VII. FUTURE WORK

Future work can focus on several directions to further improve the proposed fault detection system. One important area is the evaluation of the model under more diverse and realistic noise conditions. Future studies may investigate different noise profiles, such as impulsive noise, flicker noise, and varying signal-to-noise ratios, to better simulate practical smart grid environments and assess the robustness of the framework. Another promising direction is extending the current binary fault detection approach into a multi-class fault classification system capable of identifying specific fault categories, including LG, LL, LLG, LLL, and LLLG faults. Such an enhancement would provide more detailed fault information and support faster and more effective fault management in transmission networks. In addition, integrating Explainable Artificial Intelligence (XAI) techniques could improve the interpretability and transparency of the deep learning model by highlighting the most influential DSP features contributing to fault detection decisions. This would increase operator confidence and support the practical deployment and regulatory acceptance of the proposed system.

Data Availability Statement

The dataset used in this study is publicly available and was accessed from the original repository cited in the manuscript [9]. The author did not modify or restrict access to the data.

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Model Availability

The proposed transmission line fault detection model has been deployed as an interactive web application using Hugging Face Spaces for demonstration and reproducibility. The implementation is publicly accessible at: https://huggingface.co/spaces/shahinurislamkowser/Transmission_Line_Fault_Detection .

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