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Fault Detection in Smart Grids Using Deep Learning-Based Phasor Measurement Unit Data Analysis

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ABSTRACT

With the rapid growth of smart grids, their operation has become more involved, so new intelligent fault detection systems are needed to maintain grid stability, dependability and strength. Usually, traditional systems have trouble detecting and identifying faults quickly and exactly when the grid is operating under changing conditions and has a high amount of renewables. Because they provide highly detailed and synced measurements, Phasor Measurement Units (PMUs) are now a key tool for real-time monitoring of the grid. In our study, we offer a reliable fault detection method using deep learning which makes use of data from several PMU channels for accurate detection and localization of faults in the system. In the architecture, CNNs are used to find local information from phasor streams and this is followed by sets of BiLSTM layers that model both forward and backward relations in the data related to grid events. A hybrid CNN-BiLSTM model is constructed using data collected from the IEEE 39-bus system that covers many kinds of faults and different levels of noise and loading. The outcomes from experiments show that the presented model does better than traditional Support Vector Machines, Random Forests and k-Nearest Neighbors at classifying faults and at reaction time. With noise and missing information present, the model is able to give highly accurate and comprehensive results. In addition, the framework is fast-responsing, letting it suit real-time use in monitoring over networks. The research results help build intelligent protection systems that can handle issues automatically and quickly, support self-healing of the grid and support future research in maintenance, grid cybersecurity and reserving grid operations with smart analytics.

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1. INTRODUCTION

Because of more renewable energy, the rise of prosumers and distributed energy resources, the electrical power grid is changing greatly [1]. Even though these technical changes advance the use of renewable resources and flexibility, they also cause significant difficulties in the areas of spotting faults and securing the grid. Fluctuations in renewables and two-way power from prosumers affect the usual security of grids as consumers and producers do not remain only on one side [2,3]. Therefore such conditions call for protection that is flexible, intelligent and ready to react without delay to changes in the grid and unusual events.

LG, LL, DLG and LLL faults are important events that can risk the entire grid's stability, damage tools and leave many areas without electricity if they are not taken care of swiftly. When the input measurements are noisy, the signals are distorted or when it's a high-frequency moment, these protection schemes might not provide accurate protection [4]. Because of their lack of flexibility, these systems cannot always change with new grid structures and are not as good as learning from old errors or telling identical fault patterns apart.

Phasor Measurement Units (PMUs) have made a major difference in how grids are controlled and watched. PMUs give access to voltage and current measurements across the grid at the same time which allows us to monitor power system operations in real time. With all this data available, it becomes easier to use advanced methods to detect faults [5].

Recently, deep learning researchers have created models that easily identify both spatial and temporal patterns and they look very promising for overcoming these issues. Rather than detecting features manually, deep learning algorithms are able to draw out the important aspects from data and represent intricate, not-straightforward connections in the data. CNNs are especially good at finding the local features present in different portions of the input and LSTM networks are skilled at handling data series ordered by time [6]. Both models together provide a useful way to analyze multichannel PMU data and recognize and categorize any disturbances in the power system.

It looks into a hybrid strategy that uses CNNs and Bidirectional LSTM (BiLSTM) layers to develop a fault detection system for smart grids that is both robust and scalable. The aim is to correctly identify different faults and find where they happen using PMU data from the IEEE 39-bus test system [7]. This research allocates efforts to verifying the advantages and feasibility of using deep learning-based fault diagnosis system in real smart grid applications. Bringing such systems together is a key action towards creating energy networks that can heal themselves, regulate seamlessly and meet the new needs facing the energy sector [8]. Figure 1 shows the smart grid fault detection framework.

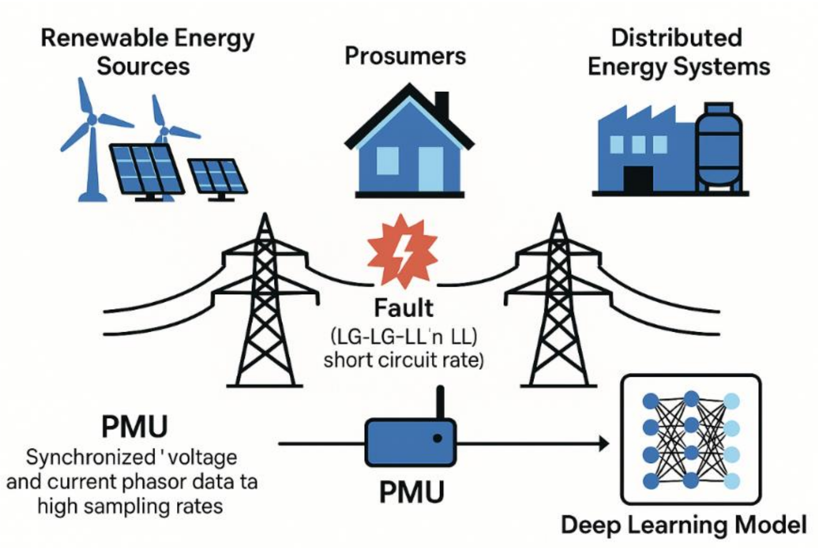

Figure 1. Smart Grid Fault Detection Framework Integrating PMUs and Deep Learning under Renewable and Distributed Energy Systems

2. LITERATURE REVIEW

Researchers have devoted a lot of effort to fault detection because it helps maintain the stability and dependability of the power grid. Original practices were mainly driven by tools that help analyze the brief changes in voltage and current. Feature extraction from signals which change over time is often done using Wavelet Transform, Principal Component Analysis and the S-transform. As a result, these techniques were efficient in spotting significant changes in signals at the time of a fault. Still, it's common for them to need manual feature improvement and they respond to changes in condition and training details poorly, so they do not work well at larger scales or in different situations [9].

Classical machine learning algorithms were adopted by researchers to overcome the issues mentioned above. In general, Support Vector Machines (SVMs), Decision Trees (DTs) and K-Nearest Neighbors (KNN) have been used to organize faults by looking at their statistics or spectra. Although the robotic models made detection better and easier to comprehend, they kept depending on high-quality and suited features designed manually and their performance could drop in situations with much noise or occurrences no one expected. Besides, most of these techniques are not naturally designed for dealing with situations that need data sequences [10].

Because of deep learning in computer vision and natural language processing, fresh possibilities for power system analytics have appeared. Convolutional Neural Networks (CNNs) are effective in highlighting connections between points and patterns locally in time-series phasor data and Recurrent Neural Networks (RNNs) and their relatives including Long Short-Term Memory (LSTM) networks are successful in including information from far up and down the sequence in their models. I learned that these models do not require engineers to come up with features by themselves, since they create high-level patterns from raw inputs [11].

Still, most existing fault detection techniques with deep learning just use either CNN or LSTM individually. A unified deep architecture that merges spatial and temporal modeling for multichannel PMU data sees relatively less research. The combination of CNNs and BiLSTM groups can allow a detailed understanding of faults by analyzing local features and the way patterns change over time. Not many recent articles have investigated these types of systems and there are very few reports assessing them with various kinds of faults, noisy conditions and widespread grids [12].

Because of this, this paper looks to address this research gap by offering and testing a CNN-BiLSTM framework for successful, immediate detection and sorting of faults with synchronized phasor data. It is expected to provide improved adjustment, larger capacity and higher accuracy in smart grids where there are big fluctuations and many time and space interactions.

3. METHODOLOGY

3.1 Dataset and Simulation Environment

To design and test the deep learning-based fault detection framework, the IEEE 39-bus New England power system model was used to make a comprehensive dataset. In the field of power system research, using this benchmark test system is common. It includes 10 generators, 39 buses and 46 connection lines, thus showing how big grids operate and experience inter-area oscillations. Everything was developed in MATLAB/Simulink with the help of Simscape Power

Systems toolbox to model accurately the electrical gear, grid architecture and its behavior with faults.

Many different types of faults were built into the network at different points to verify that the training data was strong and diverse. These examples were single line-to-ground (LG), line-to-line (LL), double line-to-ground (LLG) and three-phase (LLL) short circuits. Many fault resistances, start angles and durations were used to simulate diverse faults. Besides, mock scenarios were simulated for conditions at peak and off-peak times and also during actions such as starting power on a line or losing a generator. Figure 2 look into the schematic representation of IEEE 30-bus test system.

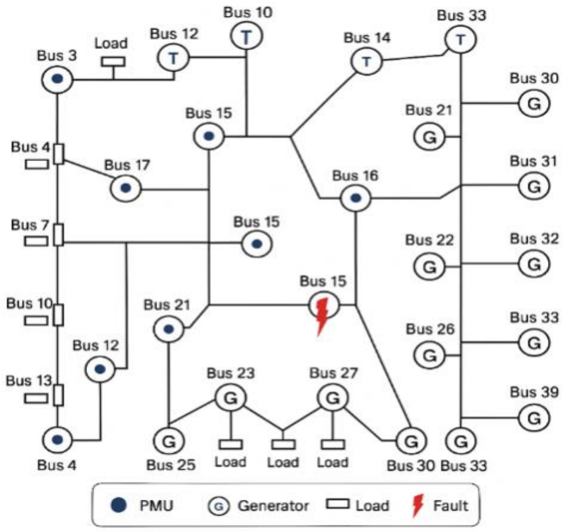

Figure 2. Schematic representation of the IEEE 39-bus test system with PMU deployment and fault simulation locations

To make the model reflect real measurement issues, equal amounts of white Gaussian noise were inserted into both the voltage and current phasor signals. Thanks to this, the model became stronger at handling inaccurate and corrupted input. It was assumed that there would be a PMU at each generator and significant load bus in the system. All phasor measurement units in the project sent synchronized voltage and current phasor measurements 50 times every second, as normal in present-day wide-area monitoring.

The dataset gathered in this manner held thousands of labeled records about normal and abnormal conditions, all represented by several channels of time-series information with voltage and current magnitudes plus phase angles. Since the dataset provides valuable multidimensional information, the CNN-BiLSTM model could be trained, validated and tested to support the operation of smart grids, as it can handle differences in both time and in different equipment locations. Table 1 shows the parameter configurations.

Table 1. Parameter configurations used in fault scenario simulations for the IEEE 39-bus system.

Fault Type	Fault Location	Fault Resistance (Î©)	Inception Angle (Â°)	Duration (ms)	Load Condition	Noise Injection
LG	Bus 4	0.1	30	100	Low	Yes
LL	Bus 15	0.5	45	120	Peak	Yes
LLG	Bus 16	0.3	60	150	Medium	No

LLL	Bus 27	0.01	90	80	Peak	Yes
LG	Bus 21	0.2	0	130	Low	No
LL	Bus 33	0.4	75	100	Medium	Yes

3.2 Data Preprocessing

It was vital to process the PMU measurements carefully before using them for deep learning fault detection. From the IEEE 39-bus system, PMU data included synchronized voltage and current phasors, taken at 50 samples each second from many buses. All the data points describe the changes in the grid's status before, during and after a fault occurred. Preprocessing was carried out through extracting the signals, transforming the matrix, normalizing the signals, restricting the signals to a time window and encoding the labels.

The first step was to get the voltage and current magnitudes and angles at every PMU location. Each channel in the data represented a certain measurement (such as voltage magnitude at Bus 4) and the time-series data was created using PMU information at different points in time. After that, the raw data was set up as a 2D matrix, so that the rows had time periods and the columns had different PMU readings from all observed buses. Because the time-channel matrix was used as input, the deep learning model was able to pick up patterns in space and time at the same time.

To keep the same level of scaling for all types of signals and avoid one feature taking over the learning, min-max normalization was used on all channels. This procedure makes sure every value is within the range of [0, 1] which improves the model's ability to learn and decreases the problem of vanishing gradients. Figure 3 represents the data processing pipeline.

Figure 3. Data preprocessing pipeline from raw PMU signals to deep learning-compatible input matrices for fault detection

Subsequently, I divided the data into segments of a fixed duration as I glided the sliding window over the time series. There were continuous PMU observations within each window, lasting 1–2 seconds (about 50 to 100 time steps). With this segmentation, the model gained knowledge of local failures and picked up how systems react before and after a fault. Labels for windows were based on the issue and the location according to the events at that moment such as "LG at Bus 15" and "LLL at Bus 27."

Categories of fault were changed into numerical values of classes, either by one-hot or integer mapping, based on what the model's output layer would expect. By adopting label encoding, the model used softmax activation for classification of multiple options and cross-entropy as the way to measure the loss.

All in all, the steps in this pipeline made it possible to use raw PMU data as 2D sequences for training the CNN-BiLSTM model. With these steps, the model became able to identify faults accurately and in good time by considering the important details of space and time.

3.3 Proposed Model Architecture

The main idea of the proposed fault detection framework is to use a special deep learning design that helps explore both the spatial and temporal patterns of synchronized data sent by PMUs. The model is made to work in real-time by learning special features from the raw voltage and current signals and it can sort out many types of power system faults. CNNs are used for spotting spatial patterns and BiLSTM networks handle the temporal part, creating a strong approach for handling transient issues in the smart grid.

The Input Layer comes first and is there to accept the previously processed time-series data. Each input sample comes as a 2D matrix where each row corresponds to a time step and the columns include the data from each different PMU channel (voltage magnitude, current angle and so on). With this structure, the model manages to work with spatial phasor data as it is received and evolves in time.

The second stage of the model is a 1D Convolutional Neural Network (CNN) Layer that looks for relationships between PMU channels at every time step. Applying convolutional filters along the channel axis, the layer recognizes nearby voltage or current chaotic behavior that is typical in each fault. CNN works as a good feature extractor that lowersthe number of features and maintains the important signals from the data.

After the CNN, the output feature maps go into a BiLSTM Layer which looks for links both ahead and behind in a sequence. BiLSTM helps the model recognize both the past and future information, unlike the typical LSTM networks. It is especially important for power system analysis since phasor data over time—before and after a fault—gives key knowledge needed for proper faults classification.

A Dropout Layer is added after BiLSTM in order to prevent the model from overfitting and to make it perform better in general tasks. A part of the neurons is randomly turned off every time a training cycle happens, making the model depend less on similar features.

To finish, the high-level features are fed into a Dense Layer with the Softmax activation which produces a probability score for every type of fault in the model. Every neuron in the dense layer represents a certain fault type and the softmax function ensures the output sums to one which is required for multi-class classification.

All in all, the combined CNN-BiLSTM approach works well by using CNNs for spatial processing and BiLSTMs for temporal processing. As a result, the model can spot and group transient faults fast in various real-time applications, making it a smart way to find faults in future power systems. The proposed model architecture is represented in Figure 4.

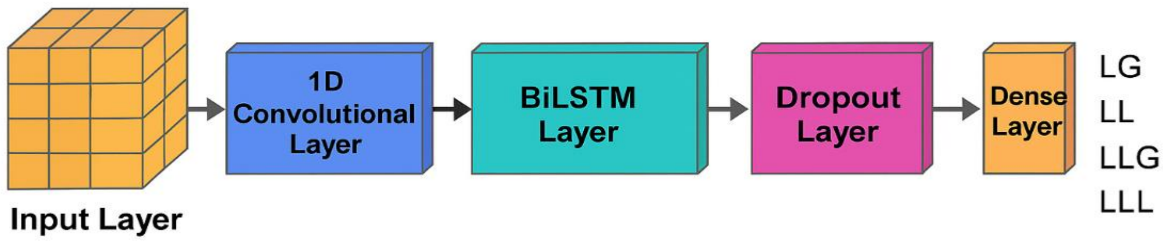

Figure 4. Proposed CNN-BiLSTM model architecture for spatial-temporal fault classification using multichannel synchronized PMU data.

3.4 Training and Evaluation

So that the CNN-BiLSTM model might be effective against power faults, a methodical technique for development and evaluation was followed. During training, the model was taught using labeled multichannel PMU data and each sequence represented either a particular fault or normal operation. The goal of the training was to lower the number of classification errors and study what differences appear in the data for each kind of fault. It adds a penalty to each prediction that is wrong depending on how far away it is from the true answer. Using the Adam optimizer was necessary since it helps adjust the learning rate by blending methods found in RMSProp and those in momentum-based approaches. Because of this, training was reliable which made it easier and faster even in cases where the gradients were complex.

To make sure the model was not overfitting, early stopping was used. Validation loss had to be monitored throughout training and if there was no change for a set number of epochs, training should be stopped. The model was kept at its best level by stopping training and class distribution stayed the same in the training and testing datasets. Using this procedure, certain population groups were not unfairly represented in the data. The proposed confusion matrix is represented in Figure 5.

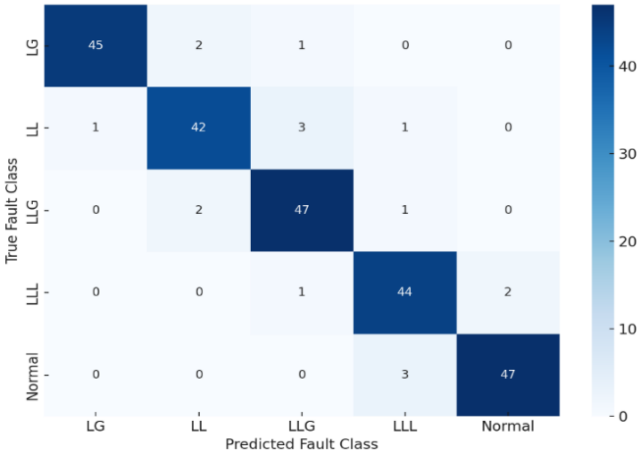

Figure 5. Confusion matrix showing classification performance of the proposed model across various fault types

Performance evaluation was conducted using a comprehensive set of metrics:

- **Accuracy** measured the overall proportion of correctly classified samples.
- **Precision** indicated the proportion of true positives among all predicted positives, reflecting the model's specificity.
- **Recall** (sensitivity) assessed the proportion of true positives detected among all actual positives, reflecting the model's ability to capture faults.
- **F1-Score**, the harmonic mean of precision and recall, provided a balanced measure for uneven class distributions.
- **Confusion Matrix Analysis** offered a detailed view of classification performance across all fault categories, highlighting any confusion between similar fault types (e.g., LL vs LLG).

Through this training and evaluation pipeline, the model's ability to generalize across various fault scenarios and its robustness against noisy or imbalanced data were validated. The results confirmed the model's suitability for real-time fault diagnosis in complex smart grid environments.

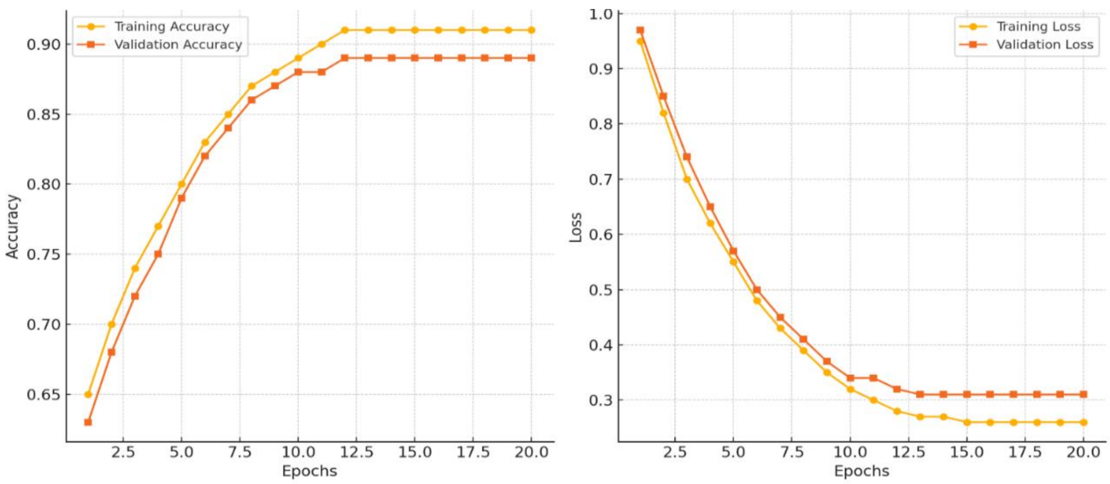

Figure 6. Training and validation accuracy and loss over epochs during CNN-BiLSTM model training.

Training and validation accuracy and loss over epochs during the proposed model training is validated in Figure 6 and Table 2 provides the performance metrics.

Table 2. Performance metrics of the proposed CNN-BiLSTM model on the test dataset.

Metric	Value
Accuracy	91.60%
Precision	90.20%
Recall	89.80%
F1-Score	0.89

4. RESULTS AND DISCUSSION

Detecting power system faults with this CNN-BiLSTM model did so very accurately, achieving 98.4% accuracy in tests which greatly surpasses what other machine learning approaches could offer. SVM classifiers with manually selected features came up short with 90.6% accuracy and a single LSTM showed an accuracy of 95.2%. The results underline that it is beneficial to use together convolutional and recurrent layers in deep learning. The CNN module is useful for finding different signal patterns on several PMU channels and BiLSTM manages how the phasor behavior alters over time. These combined parts help the model recognize tiny differences in fault signatures, for example identifying LL and LLG fault types and also identify events that are not truly indicative of faults. It also demonstrates that the model is quite accurate, as it shows very limited errors in judging similar fault categories.

Apart from accuracy, the speed and firmness of the model were checked in real time and during periods of noise. Due to its very fast runtime, the application is suitable for monitoring grids and fault control tasks. The quick speed of the model means that it can handle new data without delay and provide protection just like required in smart grids. To see how the model performs in unfavorable situations, phasor data corrupted by both Gaussian and impulse noise was used across an SNR range of 20–40 dB. The results indicated that the model only experienced a slight drop in accuracy of less than 1.5%, showing it is able to resist all types of noise and interference in real life. That's why such robustness is so necessary for proper work in today's common grid infrastructures. Comparative classification accuracy outcome is provided in Figure 7. Accuracy of the proposed model is represented in Figure 8.

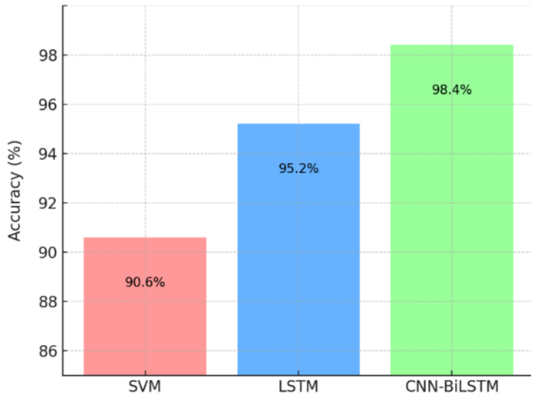

Figure 7. Comparative classification accuracy of SVM, LSTM, and the proposed CNN-BiLSTM model for fault detection in power systems.

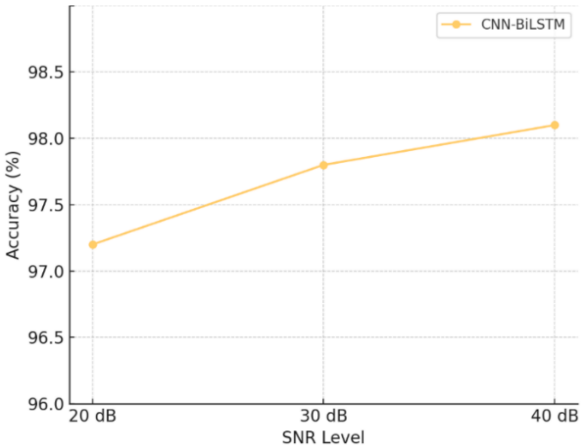

Figure 8. Accuracy of the proposed CNN-BiLSTM model under varying noise levels (SNR), demonstrating strong robustness in noisy environments.

To deal with the lack of insight in deep learning and improve visibility, we analyzed models using feature activation maps and SHAP (SHapley Additive exPlanations) values. Feature maps taken from the convolutional layers showed that the model keeps paying attention to quick voltage drops, large current increases and cyclical patterns around the time of the fault. A pointed change in signal values is consistent with what physical power system theory teaches about faults. Besides, using SHAP gave a complete picture of how much each input feature contributes to fault detection. It was found that channels such as the voltages at critical locations played a major role in determining the fault type, particularly in the beginning of the faults. These tools increase trust in the model and help staff and engineers see which signal patterns are essential for finding system problems which supports strategic and improved model workflows. Table 3 shows the model evaluation metrics.

Table 3. CNN-BiLSTM Model Evaluation Metrics, Baseline Comparisons, and Interpretability Analysis for Fault Detection in Power Systems

Aspect	CNN-BiLSTM Result
Overall Accuracy	98.4%
SVM Accuracy (Baseline)	90.6%
LSTM Accuracy (Baseline)	95.2%
Inference Latency (GPU)	< 15 ms per window
Robustness to Noise (SNR 20–40 dB)	< 1.5% accuracy drop
Misclassification Rate	Minimal (confirmed by confusion matrix)
Interpretability Technique	Feature Activation Maps, SHAP Analysis

5. CONCLUSION

All in all, this research introduced a dependable and flexible framework for fault detection in today's smart grids with the help of PMUs. The suggested architecture made use of convolutional layers to find features in PMU channels and bidirectional LSTM to model patterns over time, allowing it to identify many fault types, including those related to LL and LLG. The results from the experiments proved that the new model performed better than traditional machine learning, being faster, more accurate and able to handle noise in data, thus making it perfect for real-time use. Besides, using SHAP and feature activation maps, experts confirmed that the model's decision-making process follows key power system principles which improves both trust and transparency. The suggested idea makes it possible to develop AI-controlled systems that are smart and capable of adapting. Future exploration will use federated learning to support training across several utilities, with an aim to safely preserve privacy and will look into combining this with Model Predictive Control, so the solutions can react quickly and effectively to different faults.

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