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# Transmission Line Faults Analysis in Power System using AI Techniques

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**ABSTRACT:** Because of the rapidly expanding population and increasing energy demand, modern society depends heavily on reliable energy systems. Electrical transmission lines are a vital component of power systems, making fault analysis i.e., identification and classification is essential for improving system protection and reliability. In this study, two Artificial Intelligence (AI) techniques—Artificial Neural Network (ANN) and Convolutional Neural Network (CNN)—are used for transmission line fault identification and classification. MATLAB – Simulink model is used to study different fault conditions. The performance of the proposed models is evaluated using parameters such as accuracy, precision, recall, F1-score, ROC curves, and AUC. Simulation results show that both ANN and CNN achieve high accuracy in identifying and classifying faults. ANN provides reliable performance with simpler implementation, while CNN performs automatic feature extraction with higher complexity. Thus, both techniques are effective and suitable for transmission line fault analysis, ensuring dependable and accurate results.

**KEYWORDS:** Fault analysis, Transmission Line, Mean Square Error (MSE), Artificial Neural Network (ANN) and Convolutional Neural Network (CNN).

## I. INTRODUCTION

Energy systems are essential to all facets of society due to the expanding population and the need for energy. Due to the need for energy, especially in the sectors of industry, transportation, and domestic life, energy Systems are vital to every aspect of civilization. Electric transmission lines are a vital component of the electrical power system.

Therefore, anticipating and identifying the types and locations of faults is crucial to develop the protection strategy for the electrical system and enhancing its dependability . It reduces the time required for a particularly long transmission line, improving the efficiency and reliability of the entire power system.

Transmission line protection systems typically work by locating the fault and isolating only the impacted region. Inspections of the electrical system's component parts are carried out to increase power systems' dependability.

As distributed energy generation grows, so does the need for smart grid monitoring, control, and protection. Because smart devices are so widely used, the electrical grid is now far more dependable and flexible. Placement, categorization, and fault detection are crucial in power systems to guarantee that any issues are fixed right away and that the smart network is restarted as soon as feasible.

The microgrid requires quick and flexible fault classification processes because of the constraints of kinetic energy storage and the dynamic responsiveness of electronic power converters in distributed power systems. Rapid power system recovery and fault root cause investigation depend heavily on the detection and categorization of transmission line faults.

Because deep learning approaches can automatically identify representative features for fault identification from large datasets, they offer considerable advantages. Strong machine learning methods for fault prediction can be used to improve the protective procedures of the power transmission system. Algorithms and models based on artificial

intelligence are becoming more and more common and crucial for streamlining procedures and improving plans to satisfy growing energy demand. One of the key forces behind intelligent electrical power systems is still machine learning. The aforementioned demonstrates the growing interest and rapid expansion surrounding the use of machine learning techniques to successfully address the various technological challenges related to the smart grid. When it comes to power system issues like operation, protection, control, planning, and diagnosis, artificial intelligence is crucial. Research on identifying transmission line faults has begun, according to the literature. Transmission line fault conditions are commonly classified using deep learning techniques. The deep learning-based fault detection methods now in use need the collection of large amounts of data under a variety of failure scenarios.

A study addressing the fault scenario resulting from missing sections in insulator chains is employing these techniques. Machine learning-based techniques and methods for measuring energy system resilience have been used to evaluate the degree of resilience of future sustainable energy systems.

In addition to reviewing and analyzing the body of research in this area, a study was conducted to look at the possible function of artificial intelligence in electrical system fault diagnosis operation. MATLAB Simulink was used to create nominal operating and to collect fault voltage and current data from transmission line for 10 distinct fault categories. Artificial Intelligence (AI) techniques were then used to conduct research on abrupt fault identification and classification. Convolutional Neural Network and artificial neural networks were used in a study on the categorization of faults in power systems.

It offers an automated fault detection system that overcomes the shortcomings of conventional fault detection techniques by fusing machine learning models with real-time, state-of-the-art fault detection sensors developed by the Technical University of Ostrava. A new fault identification technique based on deep reinforcement learning (DRL) is being researched in the field of fault detection in order to improve the capabilities of intelligent approaches and eliminate reliance on massive volumes of labeled data.

Using deep learning techniques, an alternative approach to transmission line fault classification focuses on examining five distinct types of short-circuit faults in power systems. Radu-Adrian and Maria Cristea were able to improve transmission system efficiency and avert major damage by employing fault detection and classification techniques. Examining the articles makes it evident that the primary study issues are fault categorization and detection displays some of the research that makes use of machine learning techniques. This is how the remainder of the paper is structured. The actual experimental and simulation data used in this study, the suggested deep learning model design of the related neural network model, and the definition of parameters and evaluation standards are all covered and then the experimental findings and their interpretation are presented.

Artificial neural networks (ANN), An AI technique, they learn directly from data, which makes them incredibly adaptable and efficient for tasks involving fault identification. ANN systems are trained using large datasets containing a range of fault condition events. Because it automatically adjusts its internal parameters to identify patterns in the data, this training enables the network to detect and categorise faults.

ANNs are very useful in transmission line systems, where faults can vary greatly and don't always follow expected patterns, due to their ability to self-learn. An ANN's structure consists of an input layer, one or more hidden layers, and an output layer. The input layer receives the data (voltage and current sensor readings), which is then processed by the hidden layers, which employ activation functions to identify complex patterns. After being trained, the ANN can accurately detect and categorize faults in real time. Because ANNs can automatically learn from data, they provide flexibility and dependability in addressing power system issues, making them the ideal solution for fault identification and categorization.

A Convolutional Neural Network (CNN) is an advanced artificial intelligence (AI) technique widely used for feature extraction and pattern recognition, particularly in complex datasets. Unlike traditional neural networks, CNNs automatically learn spatial and hierarchical features through convolutional layers, which apply filters to the input data, followed by activation functions such as ReLU to introduce non-linearity. Pooling layers may also be used to reduce dimensionality while preserving important information. Due to their ability to capture intricate patterns with minimal

manual feature engineering, CNNs are highly effective for tasks such as fault detection and classification in power systems, where accurate identification of subtle variations in signals is essential.

## II. MATERIALS AND PROCEDURES

### II.I. Sources of Data

Datasets can be created artificially in the literature for offline model training.

Instead of utilizing actual field data, datasets are frequently created from simulated power systems. One example is the acquisition of a dataset that includes ten different categories of short-circuit fault classes—AB, AC, BC, ABG, ACG, BCG, AG, BG, CG, and ABCG through the use of simulation. as seen in Fig 1. The LLL fault is the only one of these that is symmetrical; the others are asymmetrical . All faults in each group except LLL had assessed in this study; the evaluated faults are displayed in Fig.1.

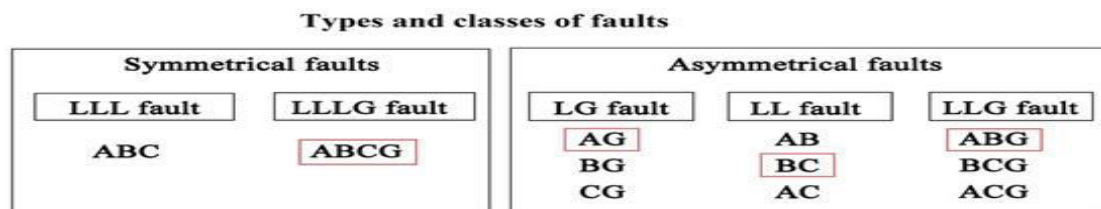


Fig.1. Types and classes of faults

## I. PROPOSED TEST SYSTEM

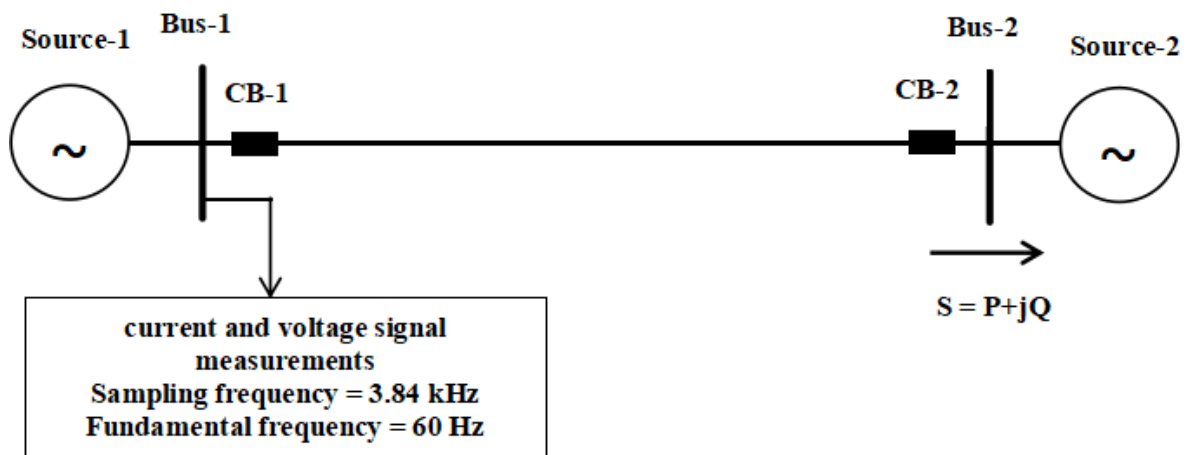


Fig.2. Proposed test system of transmission line

The test system for the two terminal transmission lines used in the proposed investigation is shown in Fig. 2. The transmission line under consideration for the planned study is connected between buses 1 and 2. Sources 1 and 2 are examples of large utility grids. The circuit breakers are CB-1 and CB-2.

Bus 1 is considered the sending end of the transmission line, whereas bus 2 is considered the receiving end. For per-unit calculations, the base voltage ( $V_{rms}$  ph-ph) and base MVA for both buses are 500 kV and 100 MVA, respectively.

However, because the transmission line is bidirectional, the proposed method is also tested under reverse power flow conditions. Table 1 [9] lists the system parameters used in the investigation. The method is tested under the line loading scenario with a load of 50 MW and 10 MVAR (inductive).

Table 1. System parameters

Sr.No.	Parameter	Magnitude of Parameter
1	Line length	150 km
2	Source-1 voltage	$500\angle 20^\circ$ kV
3	Source-2 voltage	$500\angle 0^\circ$ kV
4	Equivalent impedance of source-1	$17.177+j45.529 \Omega$
5	Equivalent impedance of source-2	$15.31+j45.925 \Omega$
6	Line Positive sequence impedance	$4.983+j117.83 \Omega$
7	Line zero sequence impedance	$12.682+j364.196 \Omega$
8	Line positive sequence admittance	$j1.468 \text{ m}\Omega$
9	Zero sequence admittance of transmission line	$j1.099 \text{ m}\Omega$
10	Line power transfer capacity	$433.63+j294.52 \text{ MVA}$

Phase-A to ground (AG), phase-A to phase-B (AB), phase-A, phase-B, and ground (ABG) and three-phase and ground (ABCG) fault events are among the fault occurrences that are being examined and this section elaborates on the specific findings about the identification of the faults that were evaluated. Fig.3 shows the voltages and currents during the various fault conditions.

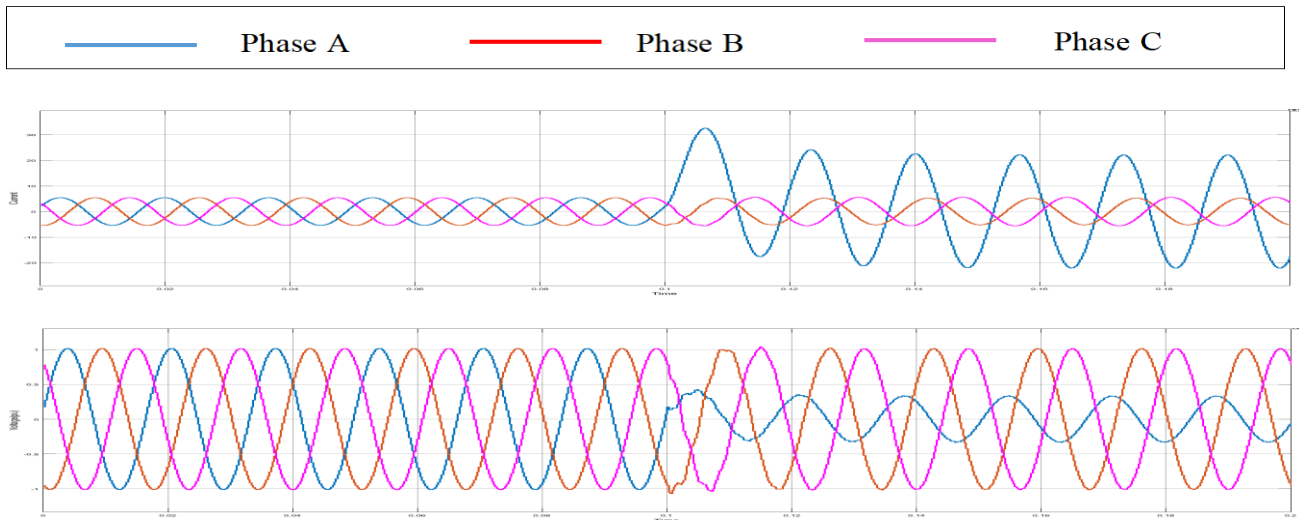
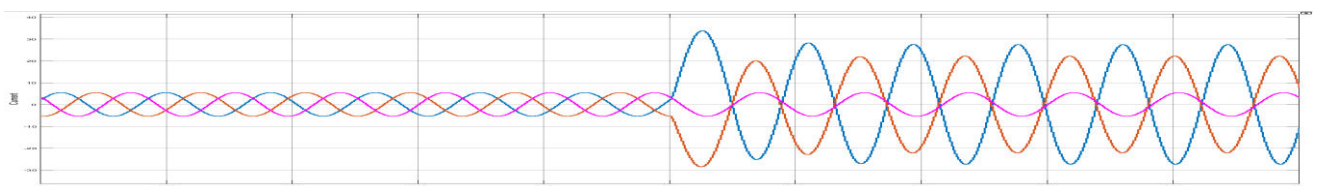


Fig.3(a). Identification of L-G (A-G) fault



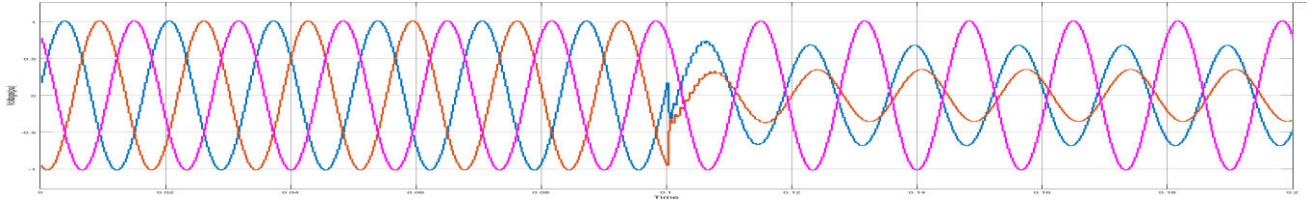


Fig.3(b). Identification of L-L (A-B) fault

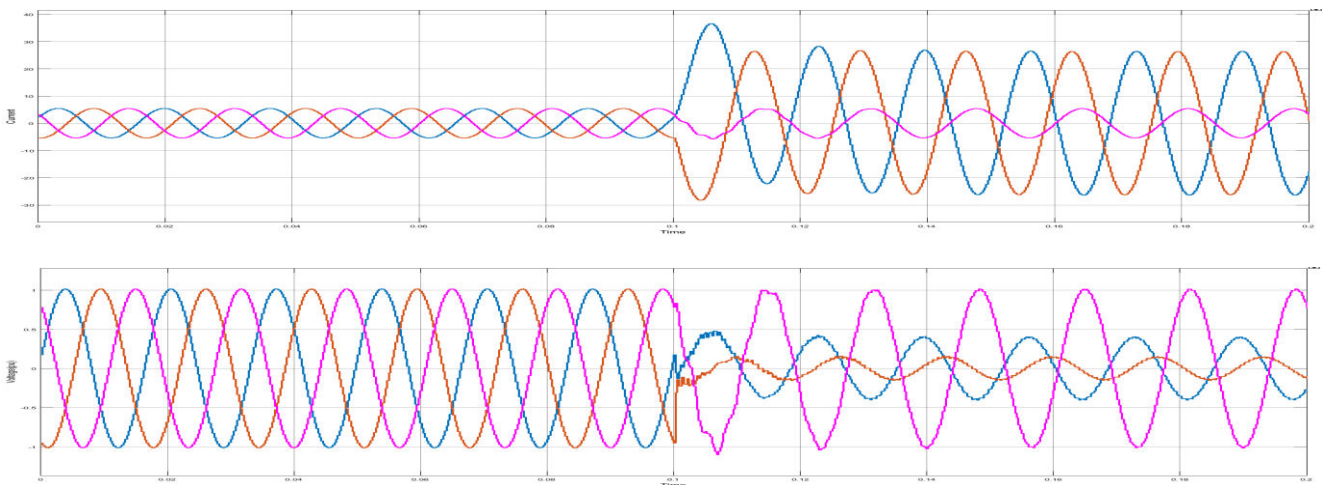


Fig.3(c). Identification of L-L-G (A-B-G) fault

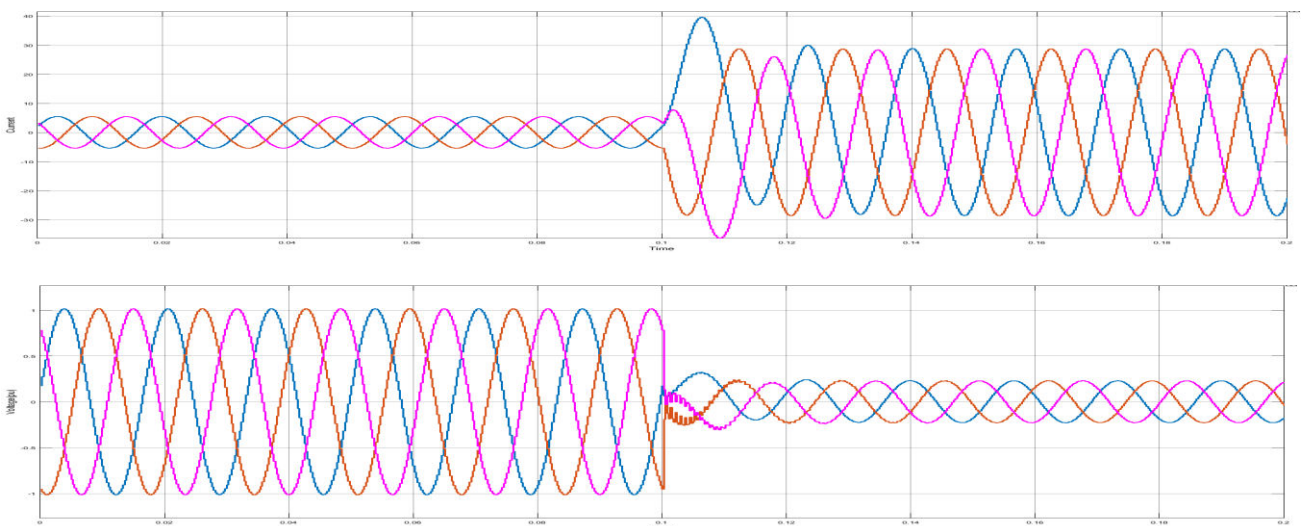


Fig. 3(d). Identification of L-L-L-G (A-B-C-G) fault

### III. A 1D CONVOLUTIONAL NEURAL NETWORK MODEL

Convolutional neural networks (CNNs) are deep learning techniques that were initially created to handle two-dimensional arrays. Multiple layers can be added to the architecture to identify different characteristics of a two-dimensional image. Different visual features at different resolutions are extracted using convolutional filters, and the output is subsequently used as the input for the layer that follows. CNN architecture consists of convolution, activation,

and pooling layers. In an effort to achieve the characteristics of two-dimensional arrays, these three layers are frequently a group of layers that are repeated. A regression layer can be appended to the end of the model to estimate continuous data in regression issues. Recurrent neural networks (RNNs) and 1D CNNs in particular are two examples of modern machine learning techniques that have shown remarkable efficacy in tackling challenging activity recognition problems, and classification assignments in the last few years [28–30]. The article's 1D CNN model's architecture is displayed in Fig. 4.

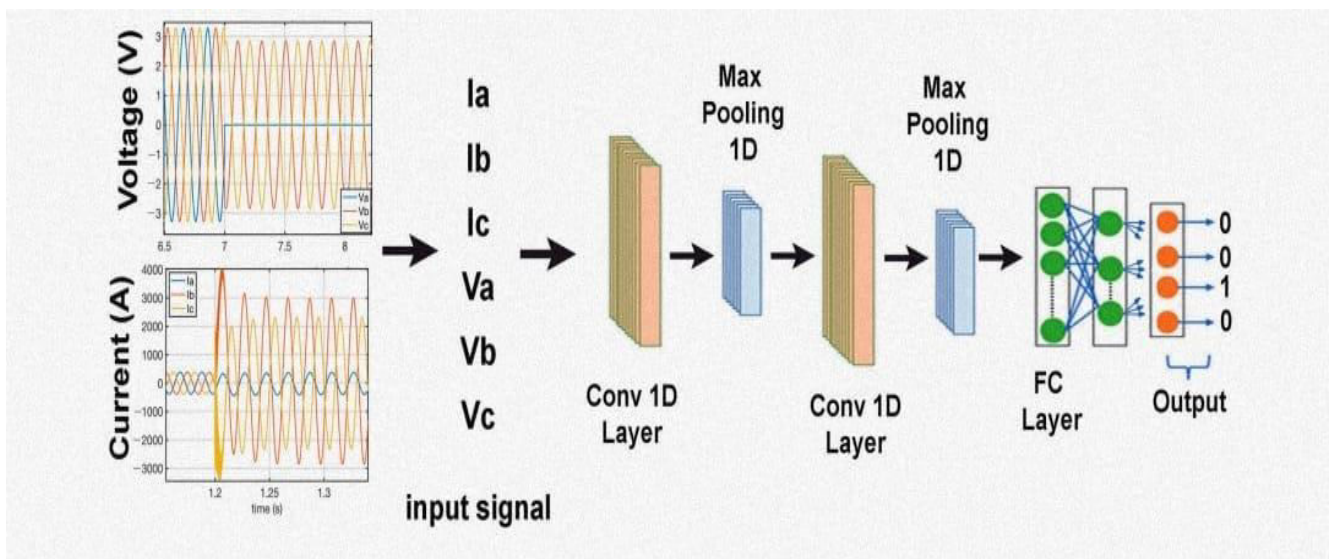


Fig.4. The architecture of a 1D CNN model

In the CNN architecture used here, no pooling layers were applied. Instead, we used convolution layers with appropriate padding to preserve the spatial dimensions of the input features. Since our input consists of only 6 features per sample (Ia, Ib, Ic, Va, Vb, Vc), applying pooling would drastically reduce the feature map size, potentially causing loss of critical information for fault classification. Hence, padding was set to maintain the original size, ensuring that all temporal and phase information is retained for accurate learning.

#### IV. ARTIFICIAL NEURAL NETWORK (ANN)

Artificial Neural Networks (ANNs) are one of the sophisticated AI techniques utilized for function approximation problems, like fault diagnosis and classification in power systems. Below is a breakdown of the primary steps an Artificial Neural Network (ANN) must follow to operate.

The first step is to import the input and target data into MATLAB. This phase ensures that the data is correctly loaded and ready for additional processing, such as training neural networks. Accurate model performance depends on proper data import. The target labels for each sort of fault, including no fault scenario, are represented by binary codes in Table 2, which are utilized as output targets.

Table 2: Target labels for every fault and for no fault

Types of fault		Binary codes			
		Phase A	Phase B	Phase C	Ground
Line to Ground (L-G) Fault	A-G	1	0	0	1
	B-G	0	1	0	1
	C-G	0	0	1	1

Line to Line (L-L) Fault	A-B	1	1	0	0
	B-C	0	1	1	0
	C-A	1	0	1	0
Line to Line to Ground (L-L-G) Fault	A-B-G	1	1	0	1
	B-C-G	0	1	1	1
	C-A-G	1	0	1	1
Line to Line to Line to Ground (L-L-L-G) Fault	A-B-C-G	1	1	1	1
No fault (Healthy TL)	No fault	0	0	0	0

The ANN architecture is designed with three main layers: an input layer representing the dataset features, one or more hidden layers for extracting complex patterns, and an output layer consisting of four neurons corresponding to fault categories. Nonlinear activation functions such as Sigmoid or ReLU are applied in the hidden and output layers to enhance the network’s ability to learn intricate relationships. As illustrated in Fig. 5, the structured arrangement of input, hidden, and output layers plays a crucial role in accurate fault classification. For training, the dataset is divided into training (40%), validation (40%), and testing (20%) subsets to ensure proper learning and generalization. The network training is carried out using the Levenberg–Marquardt algorithm, which enables fast convergence by iteratively adjusting weights and biases. During training, validation data is continuously monitored to prevent overfitting and ensure that the model captures generalized patterns rather than memorizing the training data.

After training, the ANN model is evaluated using unseen testing data to verify its generalization capability. Key performance metrics such as regression (R) value, mean squared error (MSE), and error histograms are analyzed, where a high R value (close to 1) and low MSE indicate strong prediction accuracy. The regression plot (Fig. 6) shows the relationship between actual and predicted outputs, while the error histogram (Fig. 7) represents the distribution of prediction errors. Additionally, the performance plot (Fig. 8) illustrates training and validation errors across epochs, helping assess convergence and detect overfitting. Finally, the trained Feed Forward Neural Network is implemented in a Simulink environment, as shown in Fig. 9, where it is integrated into a Neural Network block for real-time fault detection and classification, enabling effective simulation-based prediction. Unseen data is applied to it for fault classification.

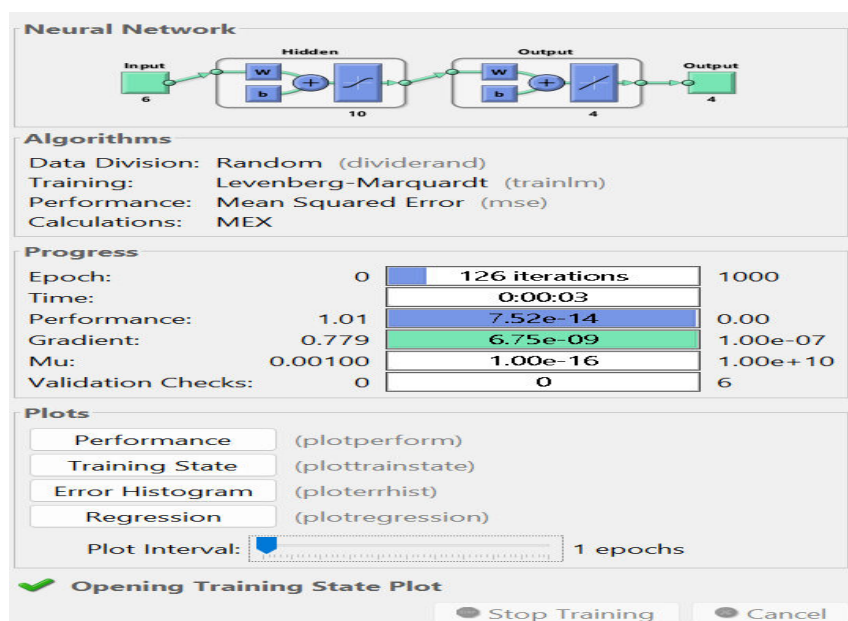


Fig.5. Network Architecture Design

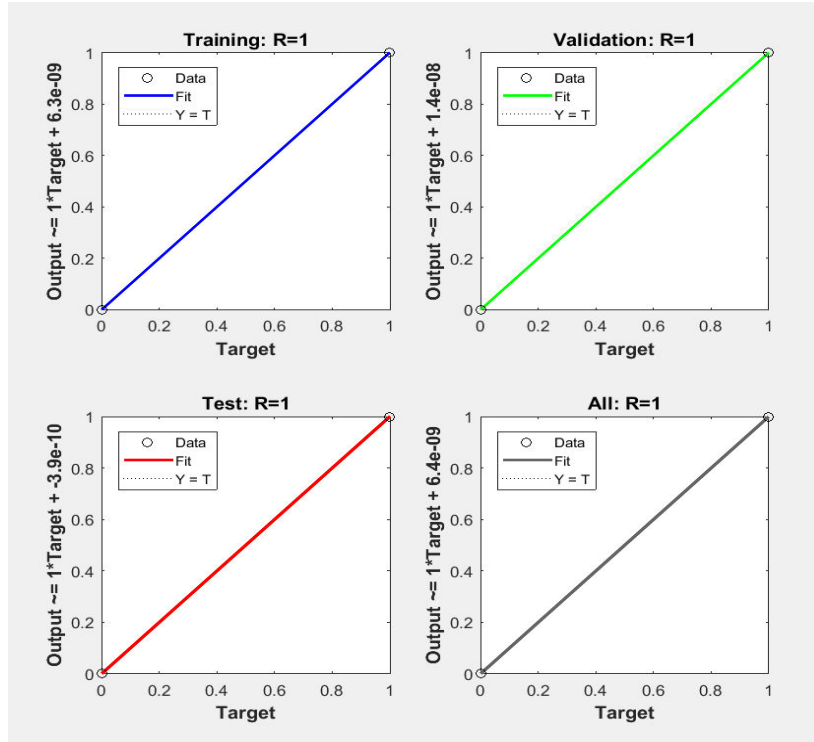


Fig.6. The regression plot

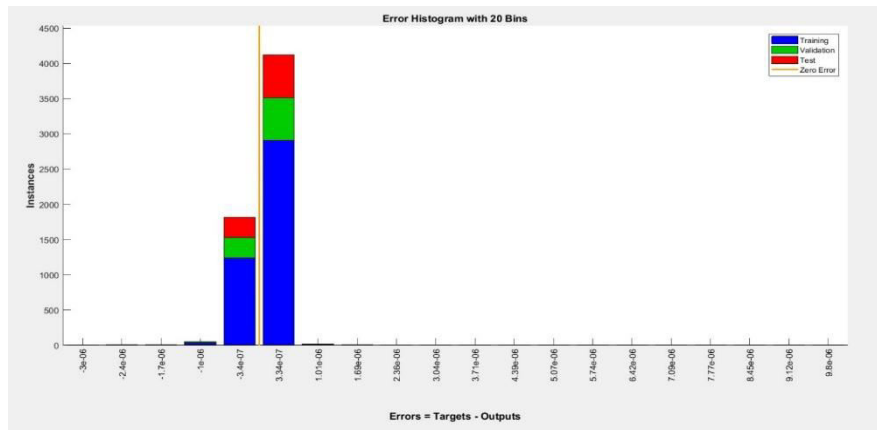


Fig.7. The error histogram

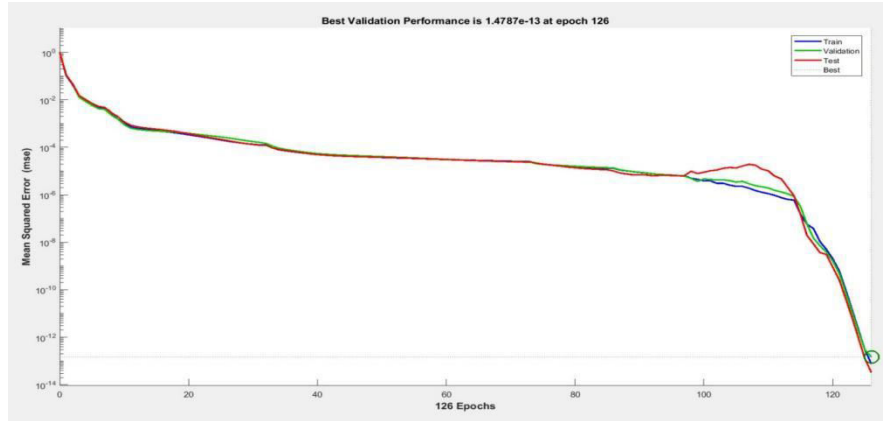


Fig.8. The performance plot

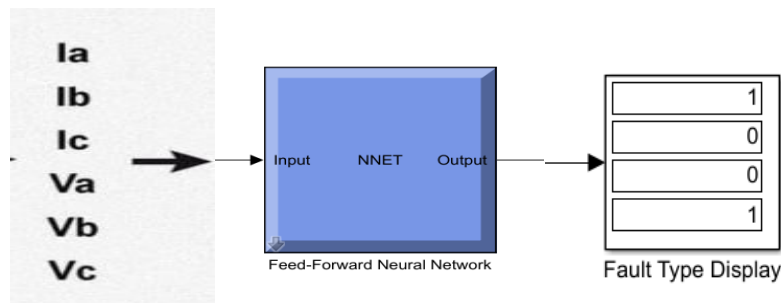


Fig. 9. Trained ANN Model

### VI.I. Evaluation Standards

Various performance criteria are employed in the literature to assess the accuracy of various models for classification. The area under the receiver operating characteristic curve (ROC AUC) is now recognized as the standard metric for evaluating binary classifications in the majority of scientific fields. One common use of computational statistics is binary classification.

Accuracy (Acc) is the ratio of the sum of correct predictions to the total samples of dataset.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \%$$

Precision (P) is the ratio of correct predictions of the positive class to the total positive predictions

$$P = \frac{TP}{TP+FP}$$

The ratio of accurate positive class predictions to the total of accurate positive class forecasts and wrong negative class predictions is known as recall (R), or sensitivity.

$$R = \frac{TP}{TP+FN}$$

A weighted average of recall and precision makes up the F1 score. Generally speaking, the F1 score is more important than accuracy, especially if the underlying dataset has an unequal class distribution.

$$\text{F1-score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

A machine learning classification problem's performance is evaluated using the confusion matrix, which summarizes accuracy, specificity, recall, and precision. It is also a useful tool for calculating the area under the ROC curve (AUC) and creating receiver operating characteristic (ROC) curves. A graphical representation of a binary classifier's characteristic capacity is the ROC curve.

### VII. RESULT AND DISCUSSION

#### VII.I. Artificial Neural Network (ANN)

Current and voltage data with a 20%-40%-40% split were used to train, test, and validate the Artificial Neural Network (ANN) model. Strong prediction accuracy is indicated by the regression result ( $R = 1$ ). Performance graphs and error histograms demonstrate low error and strong convergence. The model used unknown input data to successfully classify faults. Effective performance is validated by the confusion matrix and evaluation measures (precision, recall, F1-score).

Overall, the ANN demonstrated outstanding fault detection capacity with 100% accuracy with Test Performance Mean Square Error (MSE)  $7.3914e-06$ ; however, additional validation is advised to prevent overfitting.

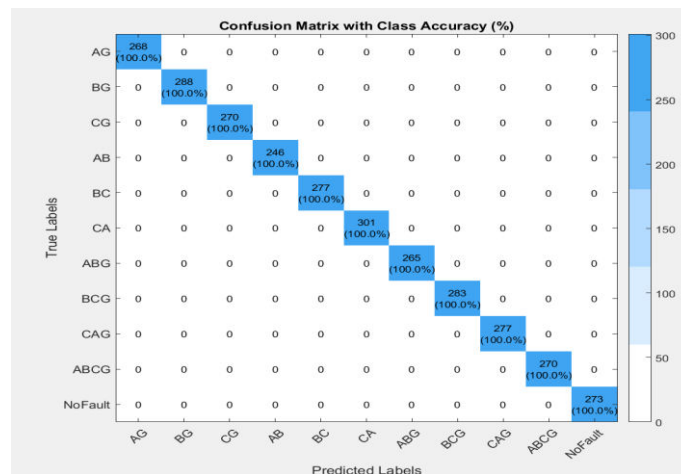


Fig.10. The confusion matrix

The confusion matrix in Figure graphically depicts the classification performance of a fault detection and classification model spanning 11 distinct classes, including various fault types (AG, BG, CG, AB, BC, CA, ABG, BCG, CAG, ABCG) and a "NoFault" condition. Each row represents the actual faults, while each column represents the expected faults. The model achieves perfect classification accuracy when all values outside the diagonal are zero and 100% of the data for each class is properly classified. The class-wise accuracy shown on confusion matrix in Fig. 10.

In addition to the derived metrics of Precision, Recall, and F1-Score, which further measure the classification performance, Table 3 lists the values of True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN) for each class. Surprisingly, the data shows that the model yielded perfect scores (1.00) for precision, recall, and total F1-score, producing zero false positives and false negatives for each of the 11 classes. This validates the confusion matrix's findings and demonstrates that the classifier not only correctly identifies every fault but also does so without overlooking any, demonstrating a very robust and reliable model performance.

Table 3. TP, FP, FN, TN, Precision, Recall, F1-Score

Class	True Positives (TP)	False Positives (FP)	False Negatives (FN)	True Negatives (TN)	Precision	Recall	F1-Score
AG	268	0	0	2750	1.00	1.00	1.00
BG	288	0	0	2730	1.00	1.00	1.00

CG	270	0	0	2748	1.00	1.00	1.00
AB	246	0	0	2772	1.00	1.00	1.00
BC	277	0	0	2741	1.00	1.00	1.00
CA	301	0	0	2717	1.00	1.00	1.00
ABG	265	0	0	2753	1.00	1.00	1.00
BCG	283	0	0	2735	1.00	1.00	1.00
CAG	277	0	0	2741	1.00	1.00	1.00
ABCG	270	0	0	2748	1.00	1.00	1.00
NoFault	273	0	0	2745	1.00	1.00	1.00

### VII.II. Convolutional Neural Network (CNN)

With a 20%-40%-40% ratio for training, testing, and validation, the Convolutional Neural Network (CNN) model was trained using the provided dataset. On transmission line fault data, the model performed well in categorization.

Accurate fault classification was indicated by the confusion matrix's strong agreement between actual and anticipated outputs. High model reliability was further validated using the ROC curve. Optimal performance was indicated by evaluation criteria such TP, TN, FP, FN, precision, recall, and F1-score.

Plots of accuracy and loss over epochs demonstrated the model's steady learning and convergence. Although additional validation is advised to assure generalization, the CNN demonstrated outstanding fault detection performance overall, achieving 100% accuracy for each fault class.

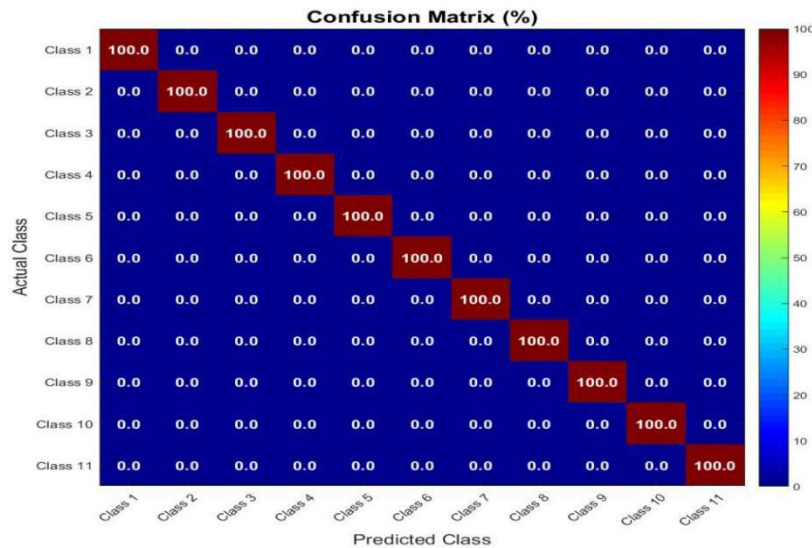


Fig.11. The confusion matrix (%)

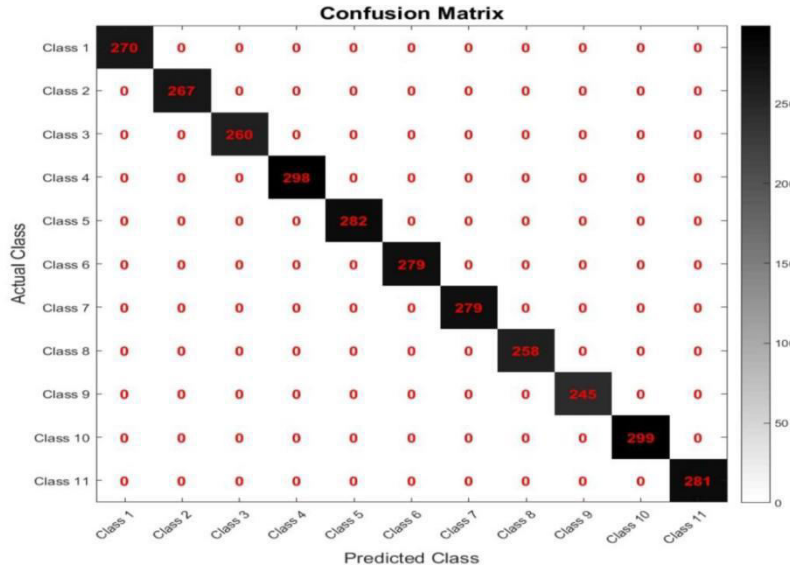


Fig.12. The confusion matrix

The confusion matrix in Figure graphically depicts the classification performance of a fault detection and classification model spanning 11 distinct classes, including various fault types (AG, BG, CG, AB, BC, CA, ABG, BCG, CAG, ABCG) and a "NoFault" condition. Each row represents the actual class, while each column represents the expected class. The model achieves perfect classification accuracy when all values outside the diagonal are zero and 100% of the data for each class is properly classified. The class-wise accuracy shown on confusion matrix in Fig.11 and Fig. 12.

In addition to the derived metrics of Precision, Recall, and F1-Score, which further measure the classification performance, Table 4 lists the values of True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN) for each class. Surprisingly, the data shows that the model yielded perfect scores (1.00) for precision, recall, and total F1-score .ROC curve, producing zero false positives and false negatives for each of the 11 classes. This validates the confusion matrix's findings and demonstrates that the classifier not only correctly identifies every fault but also does so without overlooking any, demonstrating a very robust and reliable model perform

Table 4. TP, FP, FN, TN, Precision, Recall, F1-Score

Class	True Positives (TP)	False Positives (FP)	False Negatives (FN)	True Negatives (TN)	Precision	Recall	F1-Score
1	270	0	0	2748	1.00	1.00	1.00
2	267	0	0	2751	1.00	1.00	1.00
3	260	0	0	2758	1.00	1.00	1.00
4	298	0	0	2720	1.00	1.00	1.00
5	282	0	0	2736	1.00	1.00	1.00
6	279	0	0	2739	1.00	1.00	1.00
7	279	0	0	2739	1.00	1.00	1.00
8	258	0	0	2760	1.00	1.00	1.00
9	245	0	0	2773	1.00	1.00	1.00

10	299	0	0	2719	1.00	1.00	1.00
11	281	0	0	2737	1.00	1.00	1.00

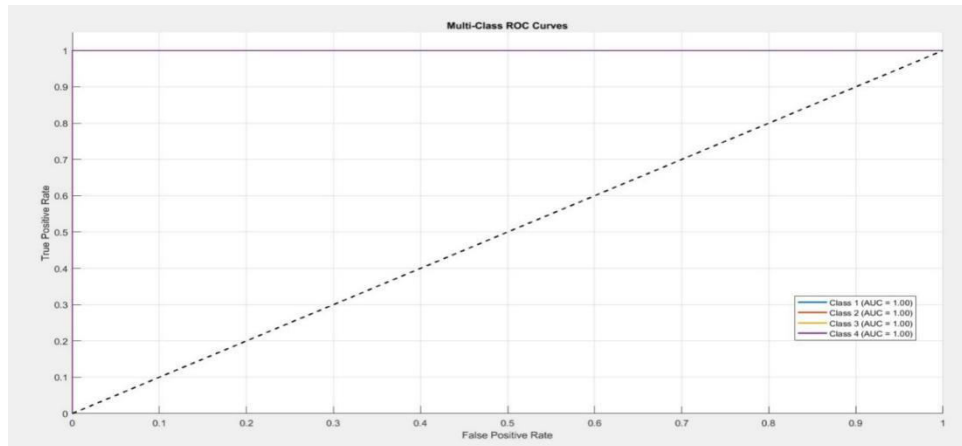


Fig.13. ROC Curve

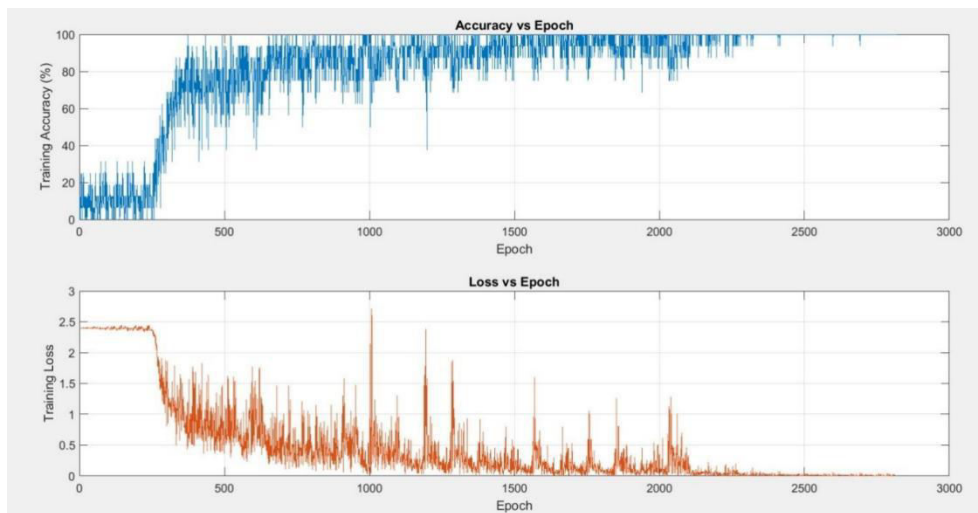


Fig.14. Accuracy and Loss Vs Epoch

Table 5. Comparison of ANN and CNN

Feature / Metric	ANN (Artificial Neural Network)	CNN (Convolutional Neural Network)
Learning Capability	Learns from data	Learns from data; excels at spatial/temporal patterns
Interpretability	Black-box model	Black-box model; more layers → harder to interpret
Data Requirement	Requires moderate to large datasets	Requires large datasets for good performance
Best Application	Pattern recognition, forecasting	Image recognition, video, spatial/temporal features
Accuracy	High (depends on training data)	High, often slightly better on structured

		data like images
<b>Input Data</b>	Raw time-domain or processed features	Structured data (images, sequences), can take raw pixels
<b>Training Time</b>	Generally, faster for small datasets	Longer training time due to convolution layers
<b>Complexity</b>	Moderate	High, due to multiple convolution + pooling layers
<b>Typical Use Cases</b>	Forecasting, fault detection, classification	Image classification, object detection, EEG/ECG patterns

### VIII. CONCLUSION

In order to detect and classify transmission line faults i.e, analysis of faults , this study examined two AI techniques Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) . The findings demonstrate the efficacy of both CNN and ANN in Fault analysis , since both reached 100% accuracy. However, CNN's architecture and computing needs are more complicated, making training and implementation more difficult. ANN, on the other hand, is more straightforward, simpler, and involves less computing work. This work can be extended to real-time fault detection, larger datasets for improved reliability, and hybrid AI models for enhanced performance in modern power systems.

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