International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 22s, 2025
https://theaspd.com/index.php

Fault Classification Method Based On Convolutional Neural Network And Random Forest Algorithms For Recognize The Power Transformer Condition

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Abstract: *In the power system, the power transformer plays an important role in transmitting voltage at various levels. Therefore, to enhance the lifespan of the power transformer, the fault recognition is done at the early stage. In order to achieve this goal, the fault detection is done using the signal processing and machine learning algorithms by analyzing the voltage and current data. In this paper, we have presented a fault classification method based on convolutional neural networks and random forest algorithms for recognizing the power transformer condition using the ensemble learning approach. Initially, in this method, the IEEE 14-bus system is designed in the MATLAB Simulink model for fault generation in the power system by measuring the voltage and current signals for different faults. After that, the preprocessing of the data is done to prepare it for the CNN and RF algorithms by performing the Butterworth filtering, normalization, and feature extraction using wavelet decomposition algorithms. Then, RF and CNN algorithms are trained and tested for fault classification, and final classification is determined by performing the voting classifier algorithm. The result indicates that the proposed method accomplishes the accuracy value of 0.9983, F1-score value of 0.9867, and MCC value of 0.9860. The key finding of the proposed method is that it determines the type of fault and helps in timely maintenance to prevent the major breakdown in the power transformer.*

Keywords: *Classification, CNN, Deep Learning, Fault, Machine Learning, Power Transformer, RF.*

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1. INTRODUCTION

Power transformers are essential parts of electrical networks because they make it possible for power to be transmitted efficiently at different voltage levels [1]. Their major job is to move electrical energy across circuits while keeping the voltage constant, which is essential for reducing losses over extended distances. Power systems are changing because of smart grids and distributed energy supplies. Because of these changes, transformers must work much harder, so they need more improved tracking and testing to keep them safe and reliable.

It is essential to conduct routine monitoring to identify early failure. Power transformers can have through issues, which can put a lot of mechanical force on the parts that are working. Furthermore, aging-related insulation deterioration may result in a decrease in clamping pressure, raising the possibility of mechanical damage [2]. Winding deformations might result from mechanical forces that exceed the transformer's design limitations. When this happens, the transformer is far less able to resist mechanical forces from a potential overcurrent because of localized electromagnetic stresses.

Nowadays, there are a lot of non-intrusive ways to monitor and diagnose power transformers that can find problems before they happen [3]. These methods may be used without disassembling transformers and assess the impact of various defects. One of the techniques utilized in the earlier research was frequency response analysis (FRA), which is now widely used in the electrical sector to evaluate the quality of transformer windings. Initial studies [4] have shown that FRA is sensitive to electrical and mechanical failure mechanisms. A power transformer's current and reference frequency response data are compared using FRA. In an ideal situation, the reference measures are taken right before the transformer is turned on. Over many years, monitoring has allowed a constant assessment of the windings' state. In cases when reference traces are not available, it is also possible to utilize traces either from sister units (identical transformers) or other phases of the same transformer (in the case of three-phase transformers).

Differences between the current measurement and the reference measurement can mean that the active parts of the transformer have been damaged electrically or mechanically. The FRA approach is more suitable to find the mechanical faults in the power transformer. On the other hand, fault classification is done using the signal processing and machine learning algorithm by analyzing the voltage and current signals to determine the various level of faults. This classification helps in timing maintenance of the power transformer. In this research article, we have presented a fault classification method to determine the various fault classes using the IEEE 14-bus. The main contribution of this research article is as follows.

1. A fault classification method is proposed for evaluate the power transformer condition using the Random Forest (RF) and Convolutional Neural Network (CNN) algorithms using the ensemble learning approach.
2. A MATLAB Simulink model is designed to generate a dataset. In this model, IEEE 14-bus was used to generate different faults. Furthermore, a preprocessing method is designed by considering the Butterworth filter, normalization, wavelet decomposition, and Fast Fourier Transform (FFT) to select the optimal features from the dataset.
3. The performance evaluation of the proposed fault classification method shows that we have achieved high values of accuracy (0.9983), F1-score (0.9867), and MCC (0.9860) over the existing approaches.

The remaining paper is presented in the following manner. Section 2 presents the related work done on the fault recognition for the power transformer. Section 3 defines the preliminaries. Section 4 presents the proposed fault classification method. Section 5 shows the results and discussion. Section 6 concludes and defines the future scope of the paper.

2. Related Work

Thomas et al. [6], presented a fault detection method for power systems using the CNN algorithm. In their work, the 1-D CNN algorithm was employed for feature extraction purposes. They have generated the dataset by considering the IEEE 14 bus, and various faults are generated in the power system. They have achieved an MCC value of 97.53%. M. Bigdeli and A. Abu-Siada [7], evaluated the power transformer condition by analyzing the frequency response. Furthermore, in their paper, they have done the clustering of the data to determine the fault type and used the GOA algorithm to determine the best parameter values of the clustering algorithm. Chothani et al. [8], presented a CNN and XGBoost technique to identify the transformer fault. In their work, a small power system was designed using PSCAD software to generate the voltage and current signal. Thereafter, these signals were processed using the CNN and XGBoost techniques. The results indicate that the technique effectively identifies faults. M. Kim and S. Lee [9], analyzed the acoustic signal of the power transformer to determine the transformer condition. In their work, the acoustic signal was processed using a Mel spectrogram. The U-Net algorithm extracted the features, and the ensemble learning approach classified the fault. Domingo et al. [10], diagnosed the fault in the transformer by processing the current signal using the Fourier transform and Hilbert transform. Furthermore, feature selection is performed using the Pearson correlation, and fault classification is done using the machine learning algorithms. The results indicate that KNN achieves an accuracy value of 83.89%.

3. Preliminaries

This section presents an overview of CNN and RF algorithms that are employed in the proposed method for fault classification purposes.

3.1 CNN

The CNN approach begins with convolution, max-pooling, and feature analysis. The results of these steps are then sent to the fully connected (FC) layer, which makes the final classification decision, as illustrated in Figure 1 [11]. This section [12] discusses more detail about these layers.

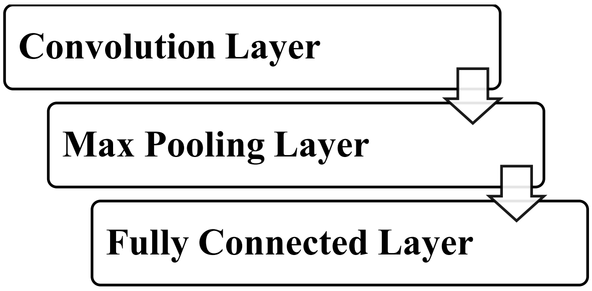


Figure 1 CNN Layers

- Convolution Layer: A convolutional neural network (CNN) has one or more convolution layers, as opposed to ordinary neural networks. Convolutional layers function as filters. Every time the filter function is applied to a neighborhood of nodes in the preceding layer, a matching set of outputs is generated. Additionally, in this layer, padding is done at the input layer's edges to make filter processing at the boundaries easier. The convolution kernel, also known as the input window, is moved to apply the kernel to every subset of nearby nodes. A convolution layer is defined by two crucial configuration hyperparameters: stride and kernel size. The kernel size shows how many inputs the convolution kernel can handle at once. The stride, on the other hand, indicates how many nodes the filter is moved by after each application. The learning ability to extract additional features may be increased by using several convolution filters (kernels) in a single convolution layer.
- Pooling Layer: The primary function of pooling layers is subsampling or dimensionality reduction. These are specialized convolution layers. A max-pooling layer sends out the most data that fits into its input area.
- Fully Connected Layer: It is crucial to have fully connected layers so that learnt characteristics may be turned into more general functionalities. By flattening the output from the preceding layer, the FC layer creates a single vector. The local characteristics are represented by a matrix or higher-dimensional map in the convolution layers that come before the FC layer. On the other hand, the FC layers include the combined and compiled data from every earlier layer in an easy-to-understand vector format. The output layer uses a Softmax function to generate the probability score for each class, which ranges from 0 to 1 [11].
- Other Layers: To increase the model's nonlinear capability, threshold layers like rectified linear unit (ReLU) layers are often used. Before applying nonlinearities, convolution layer output is commonly batch normalized. As a result of normalization, learning speeds are increased and the impact of the initially random network weights is mitigated.

3.2 RF (Random Forest)

RF is a tree-based technique that reduces overfitting and blends many DT-based classifiers to enhance DT [13-14]. As seen in Figure 2, RF trains by generating many decision trees and then forecasting the class. This model makes individual tree predictions based on the most-voted class forecast. RF is used to diagnose defects in power transformers due to its great model generalization capabilities.

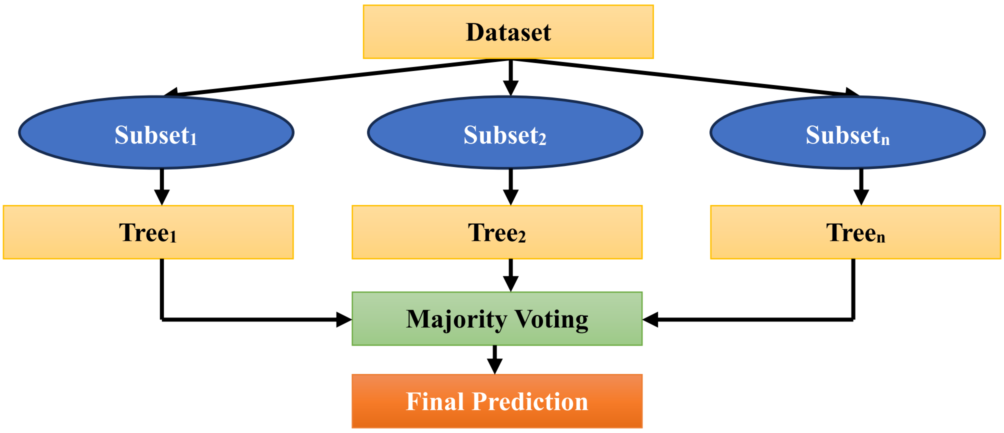


Figure 2 Structure of RF Algorithm

4. Proposed Fault Classification Method

This section presents the proposed fault classification method is designed for evaluate the power transformer condition. The key contribution of the proposed method is that it effectively determines the various fault classes by analyzing the voltage and current signals. Figure 3 shows the proposed fault classification method.

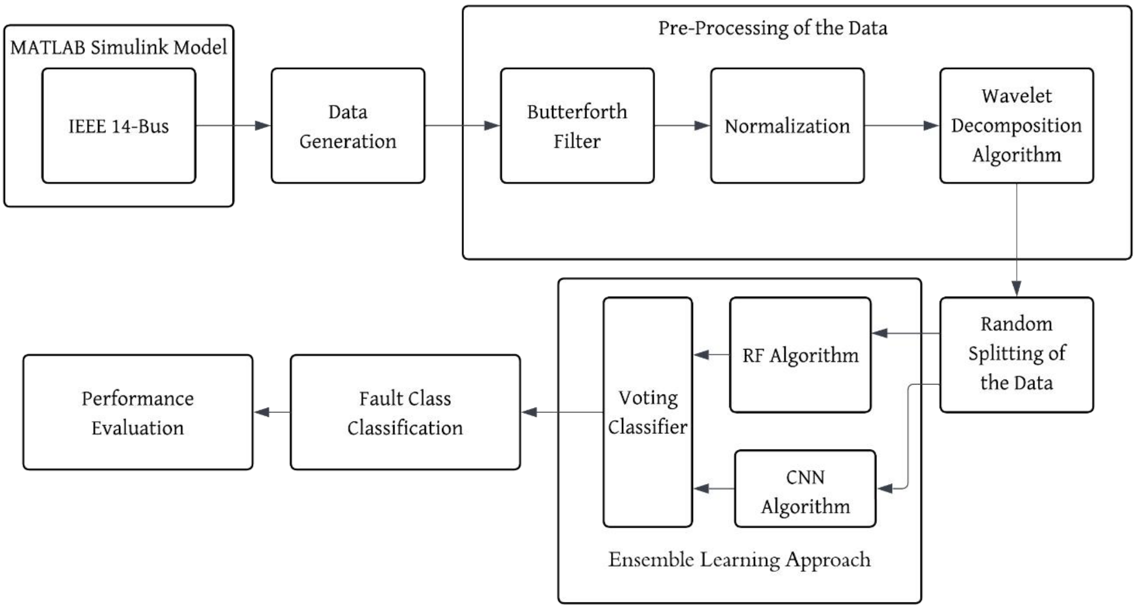


Figure 3 Proposed Fault Classification Method

Initially, in the proposed method, the IEEE 14-bus was utilized to generate the different faults for the transformer. In this research, 14 fault classes were generated by generating the fault in phases, with ground and high impedance. Thereafter, the signals of each fault, along with their classes, were stored in a database. Next, the dataset was pre-processed by passing through it the Butterworth filter, normalization, and wavelet decomposition algorithm. In the wavelet decomposition algorithm, the features were extracted using the statistical features and FFT algorithm. Furthermore, the dataset was randomly split into training and testing ratios to validate the machine learning algorithms. In this research, a 70:30 ratio was used. The data was trained for the RF and CNN algorithms by utilizing the ensemble learning approach. In the CNN algorithm, 2 convolution layers, batch normalization, and a ReLU layer were used. Similarly, one max-pooling and one fully connected layer were used for fault classification purposes. On the other hand, in the random forest, the size of the tree was taken as 100. The final fault classification was done using the voting classifier algorithm. Finally, in the last stage, the performance evaluation of the proposed method was done by evaluating the various parameters.

5. RESULTS AND DISCUSSION

This section reports the simulation results of the proposed fault classification method to show its effectiveness over the previous approaches. In this work, a MATLAB Simulink model was used for data generation purposes. After that, the data was loaded, and the fault classification method was designed and simulated in MATLAB 2018a. Furthermore, the laptop configuration that was considered for simulation purposes is an i7 processor, 16GB RAM, 1TB hard disk, and 64-bit Windows operating system.

5.1 Evaluation criteria and Performance Indices

This section initially presents the evaluation criteria for the proposed fault classification method. In this work, the sampling frequency of the data was 1000, and the fault classification was done in 14 classes. The voltage and current graphs of different classes are presented in Appendix-I. Furthermore, the optimal features from the dataset were extracted using wavelet decomposition, statistical features, and the FFT algorithm. The parameter values of the wavelet, level, and window size of the wavelet decomposition algorithm were ‘db4’, ‘3’, and ‘4’. The statistical features from the wavelet were extracted using mean, variance, entropy, skewness, and kurtosis. Furthermore, the parameter values of nfft and sample rate in the FFT were taken as 128 and 1000. After feature extraction, the data was split into a 70:30 ratio for training and testing the RF and CNN algorithms. Finally, the CNN and RF parameters were initialized, such as learning rate: 0.001, MaxEpoch: 30, and number of trees: 100. On the other hand, in this paper, three performance indices, namely, accuracy, F1-score, and Matthews Correlation Coefficient (MCC), were determined to evaluate the performance of the proposed method over the existing approaches [15]. A detailed description of these parameters is given below.

- Accuracy: Accuracy is one of the criteria used to evaluate the model's performance. It is determined using Eq. (1).

$$Accuracy = \frac{No.of\ Correct\ Results}{Total\ no.of\ Results} \tag{1}$$

- F1-Score: This parameter uses the harmonic mean of the accuracy and recall metrics to evaluate a model's performance.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{2}$$

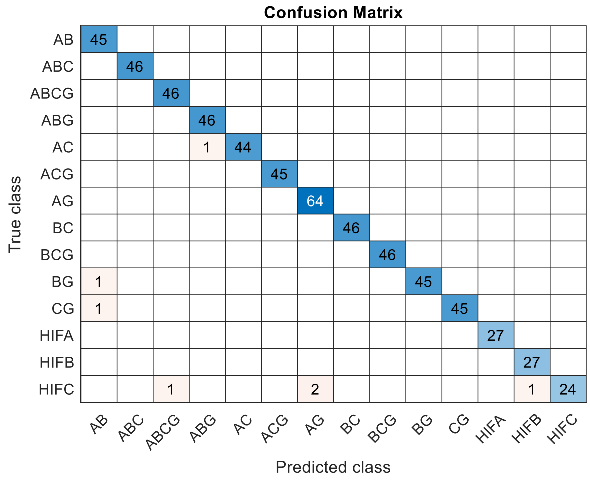
- MCC: The MCC is a newer measure that is better at dealing with class differences. The following is a formal definition of this:

$$MCC = \frac{cxs - \sum_{i=1}^{N} p_i x t_i}{\sqrt{(S^2 - \sum_{i=1}^{N} p_i^2)(S^2 - \sum_{i=1}^{N} t_i^2)}} \tag{3}$$

In the above equation, $c = \sum_{i=1}^{N} TP_i$ refer to the TP for i class. $P_i = TP_i + FP_i$ represents the total instances in which class i was properly or incorrectly categorized by the classifier, s represents the total samples, and $t_i = TP_i + FN_i$ represents the total samples in the dataset that belong to class i. The values of MCC ranged from MCC ∈ $[-1, 1]$. The MCC suggests a significant positive correlation between the true labels and the predictions for greater positive values (MCC ≈ 1). Conversely, high negative values (MCC < 0) show that the classifier recognizes the classes but consistently predicts them incorrectly (more likely due to an implementation issue). There will be no link between forecasts and real labels if the classifier is just guessing, so the MCC is (≈0). The MCC also has the advantage of being sensitive to class imbalance, which makes it useful for evaluating a classifier's performance when the dataset has such a characteristic.

5.2 Simulation Results

Figure 4 presents the graph of the confusion matrix for determining the different fault classes in the proposed method. The diagonal components in the matrix define the number of true classes to classify the different classes. Furthermore, by analyzing this confusion matrix, the other parameters are determined.



	AB	ABC	ABCG	ABG	AC	ACG	AG	BC	BCG	BG	CG	HIFA	HIFB	HIFC
AB	45													
ABC		46												
ABCG			46											
ABG				46										
AC				1	44									
ACG						45								
AG							64							
BC								46						
BCG									46					
BG	1									45				
CG	1										45			
HIFA												27		
HIFB													27	
HIFC			1				2						1	24

Figure 4 Confusion Matrix for the Proposed Fault Detection Method

Table 1 indicates the parameter values of the accuracy, F1-score, and MCC for the proposed method. The result indicates that the proposed method achieves an average accuracy value of 0.9983, an F1-score value of 0.9867, and an MCC value of 0.9860. These parameter values are near to the ideal value of 1.

Table 1: Evaluation of the Proposed Fault Detection Method using Various Performance Indices

Parameter	**Proposed Fault Detection Method**
Accuracy	0.9983
F1-Score	0.9867
MCC	0.9860

Finally, in Table 2, we have done the comparative analysis with the previous approaches that used the machine learning algorithms for fault classification purposes [6]. The result indicates that the proposed method accomplishes the highest accuracy, F1-score, and MCC parameter values over the previous approaches.

Table 2: Comparative Analysis with Previous Models

Model	**Accuracy**	**F1-Score**	**MCC**
'1-D CNN'	0.8713	0.8694	0.8588
'BiLSTM	0.8847	0.8821	0.8715
'BiGRU-Attention	0.9201	0.9195	0.8996
'BiLSTM-Attention	0.9215	0.9197	0.9021
'1-D CNN BiLSTM-Attention	0.9674	0.9621	0.9487
'NAS 1-D CNN	0.9341	0.9334	0.9199
'Xception Transformer'	0.9860	0.9858	0.9753
Proposed Method	**0.9983**	**0.9867**	**0.9860**

Figure 5 shows the comparative analysis based on the accuracy parameter with previous approaches. The result indicates that the 1-D CNN algorithm achieves the lowest accuracy value of 0.8713, whereas the proposed method achieves the highest accuracy value of 0.9983.

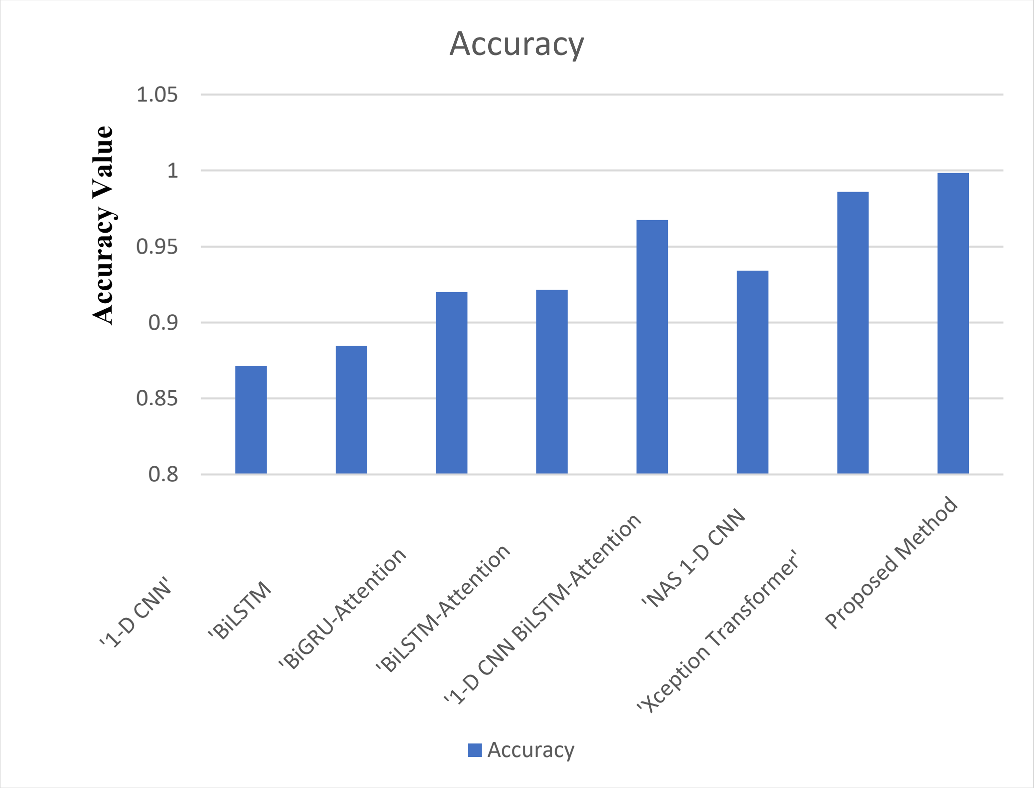


Figure 5 Comparative Analysis based on Accuracy Parameter with Previous Models

Figure 6 presents the comparative analysis based on F1-score. The result indicates that the Xception transformer and the proposed method achieve the highest value over the approaches.

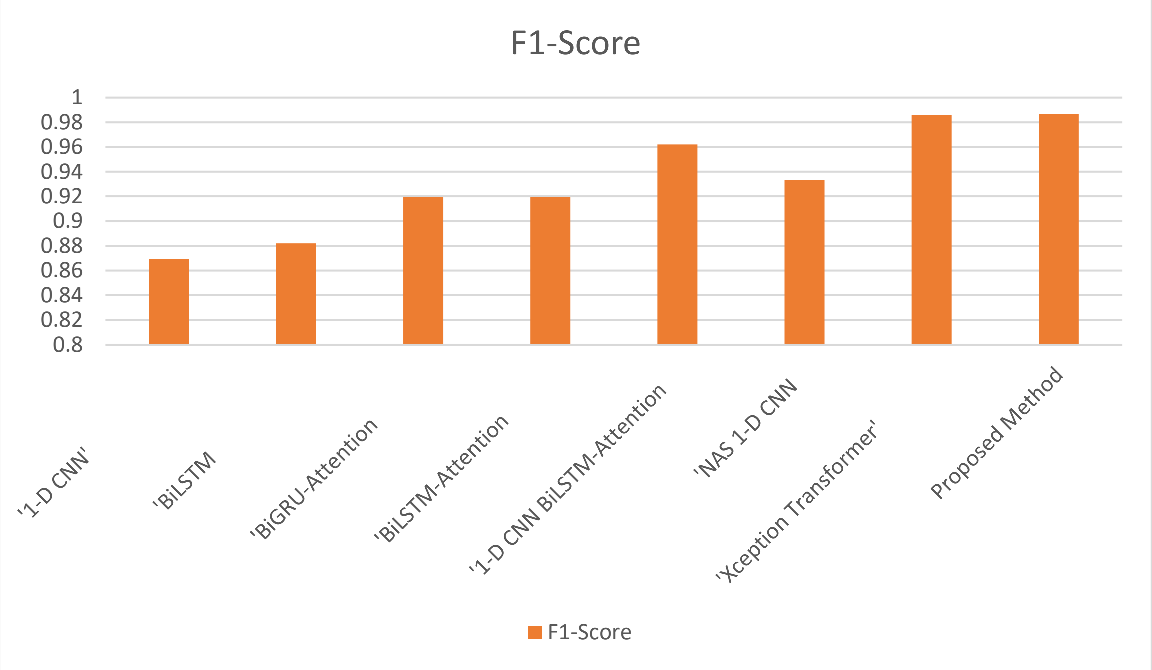


Figure 6 Comparative Analysis based on F1-Score Parameter with Previous Models

Finally, Figure 7 presents the comparative analysis based on the MCC parameter. The MCC value varies from 0.8588 to 0.9860. Furthermore, the result indicates that the proposed method accomplishes the highest value near to the ideal value of 1.

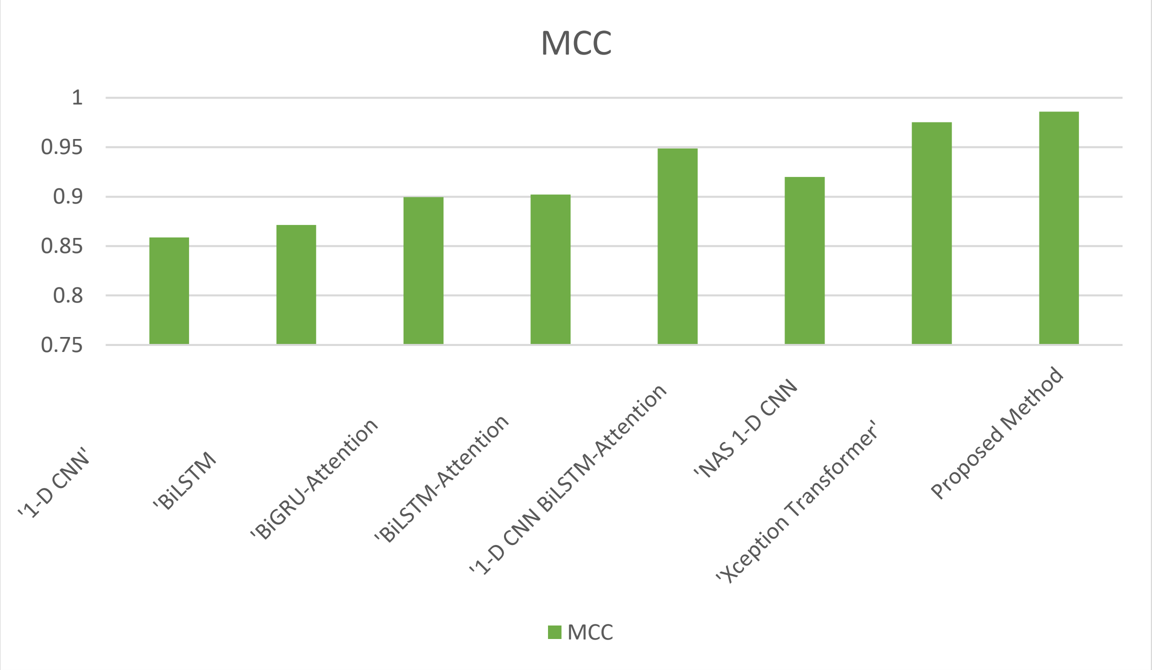


Figure 7 Comparative Analysis based on MCC Parameter with Previous Models

5.3 Discussion

The key findings from the evaluation of the proposed method are that it effectively classifies the different fault classes in the power transformer condition. The proposed method achieves this effective classification by selecting optimal features and utilizing the ensemble learning approach. On the other hand, the sample size in the proposed method is small, and it takes a high computation time to classify faults due to incorporating several algorithms.

6. CONCLUSION AND FUTURE SCOPE

In this article, we have presented an effective fault classification method for evaluate the power transformer condition using the RF and CNN algorithms. These algorithms were hybrid, using the ensemble learning approach. Furthermore, in order to train and test the RF and CNN algorithms, the optimal feature selection from the data was done using wavelet decomposition, statistical feature, and FFT algorithms. The result indicates that the proposed method accomplishes the high accuracy value of 0.9983, F1-score value of 0.9867, and MCC value of 0.9860. The parameter values of the proposed method are near to the ideal value. Furthermore, the benefit of our method is that it effectively classifies the different classes of the fault. In the future, we will evaluate the proposed method for large datasets. Besides that, the computational complexity of the CNN algorithm will be reduced by optimizing the layers of it.

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Appendix-1

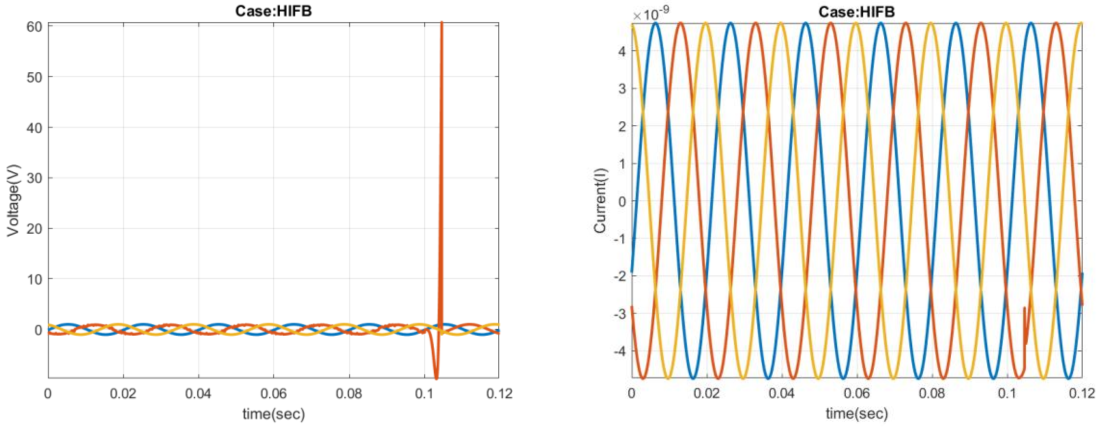

Figure A1: Case-HIFB

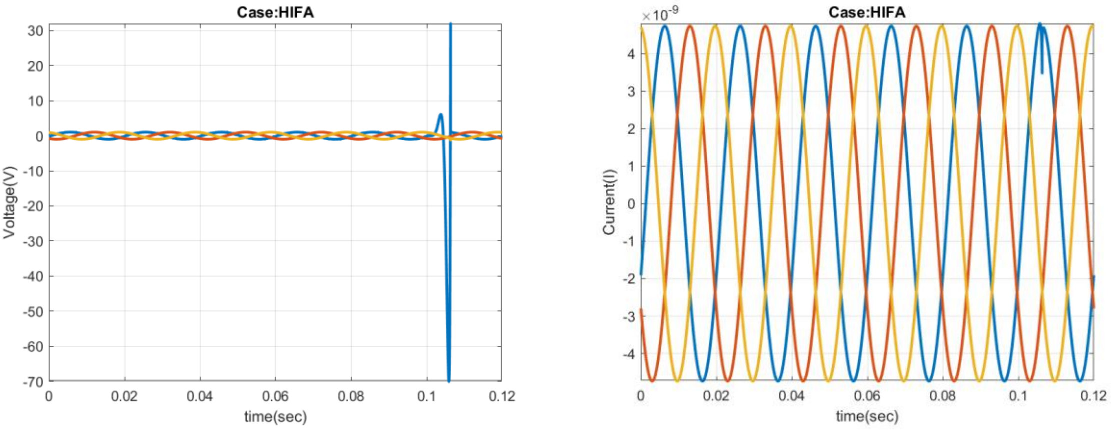

Figure A2: Case-HIFA

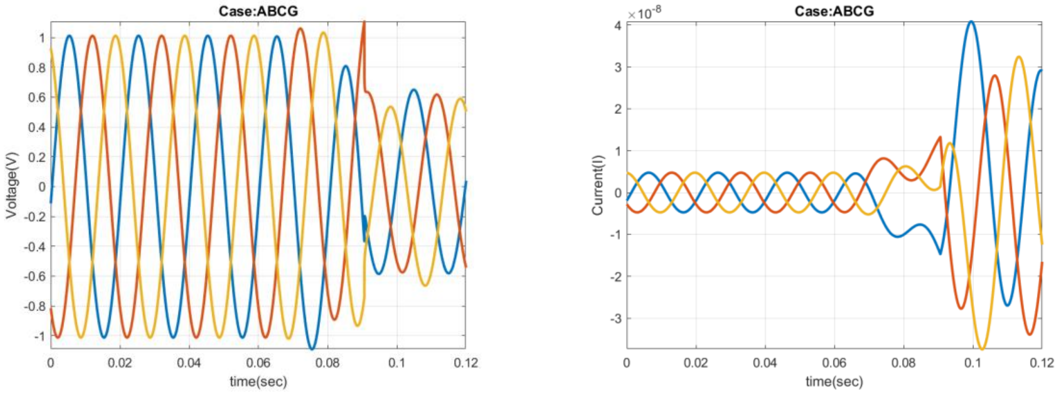

Figure A3: Case-ABCG

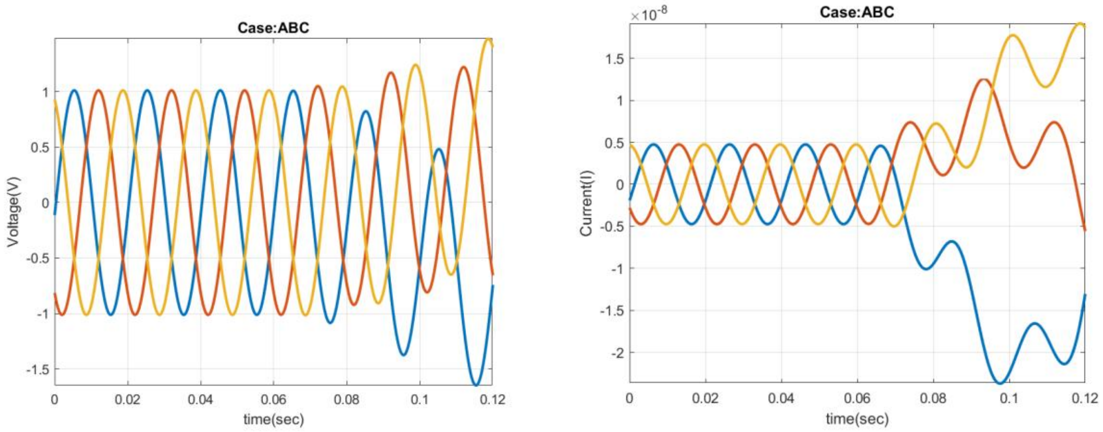

Figure A4: Case-ABC

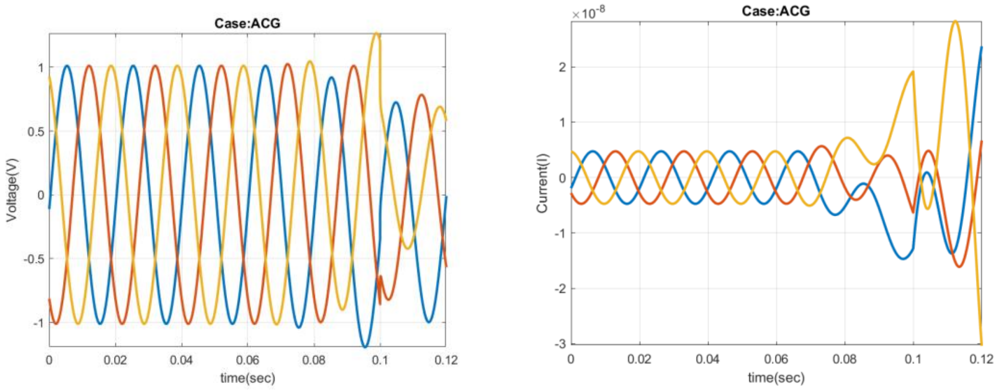

Figure A5: Case-ACG

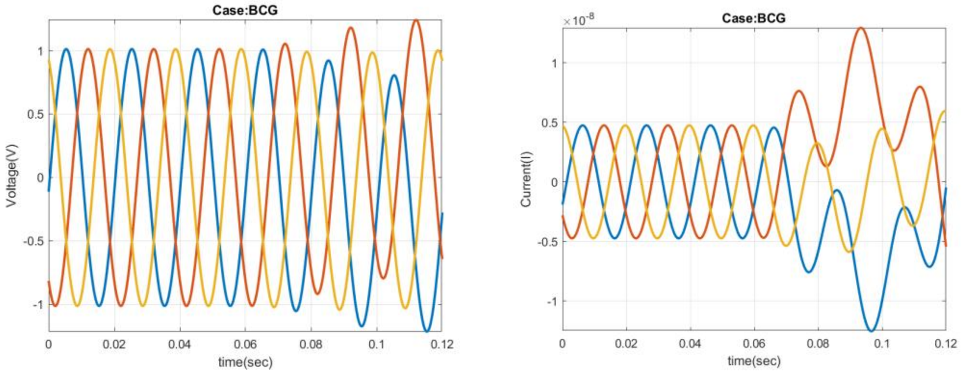

Figure A6: Case-BCG

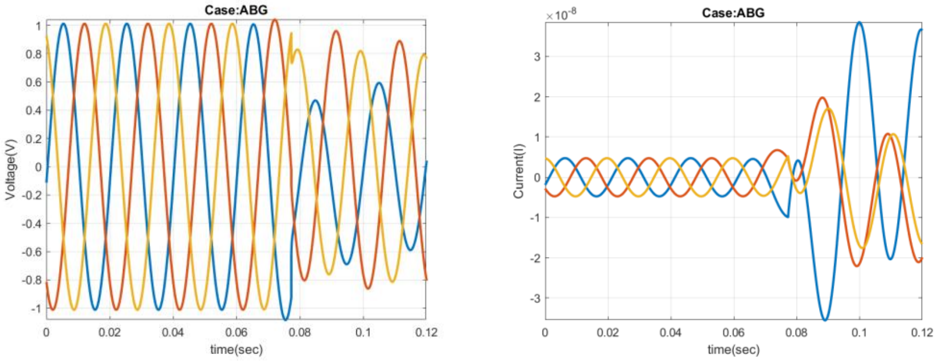

Figure A7: Case-ABG

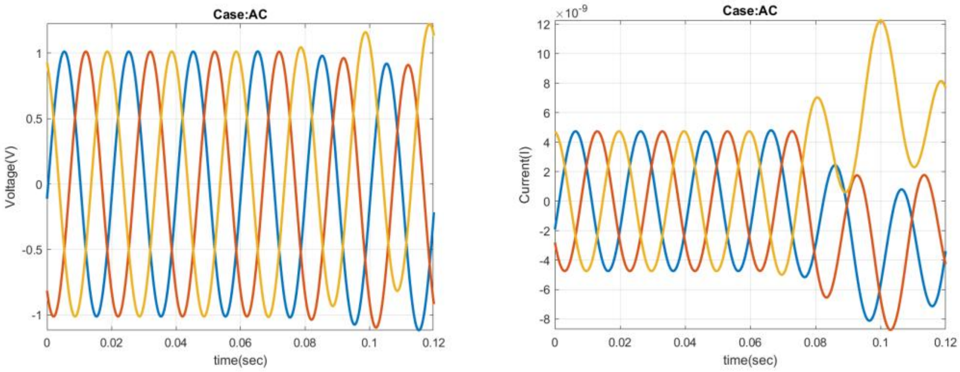

Figure A8: Case-AC

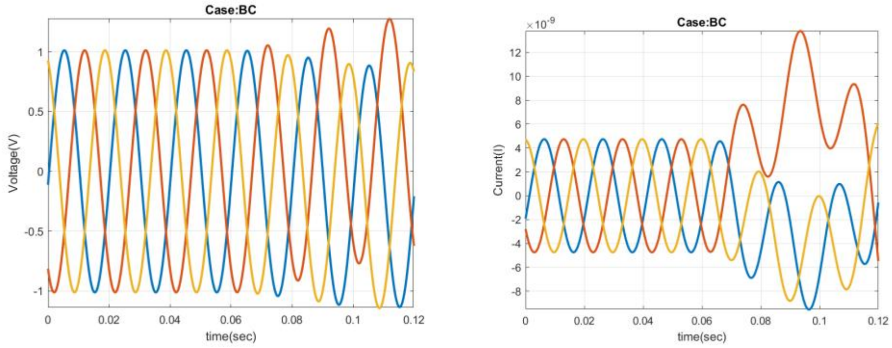

Figure A9: Case-BC

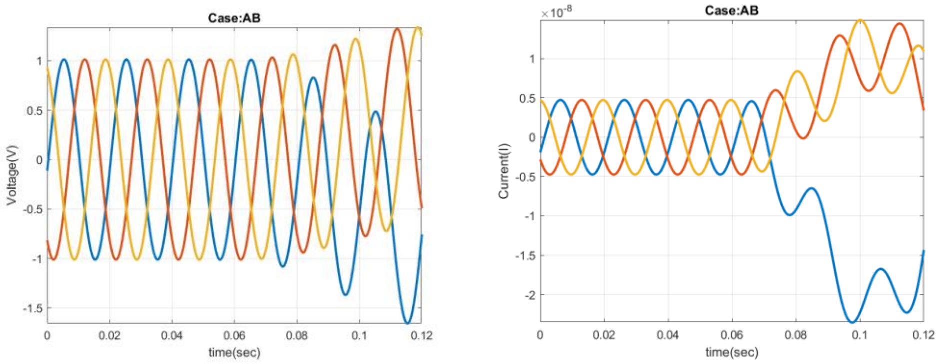

Figure A10: Case-AB

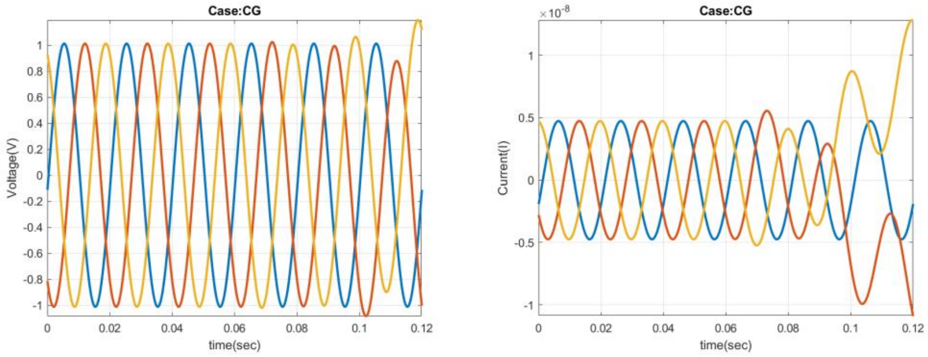

Figure A11: Case-CG

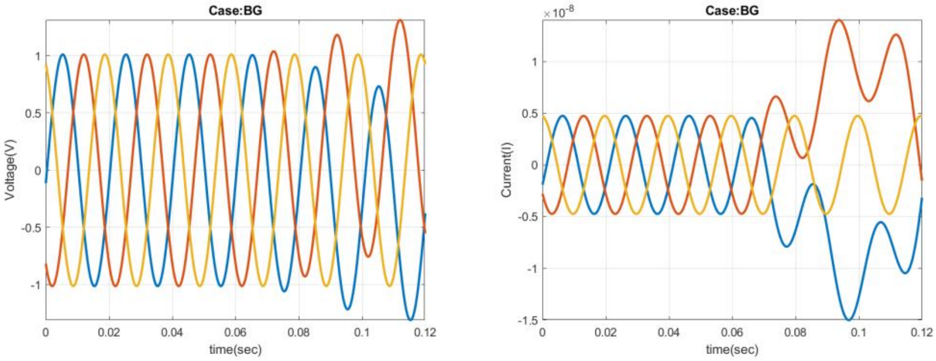

Figure A12: Case-BG

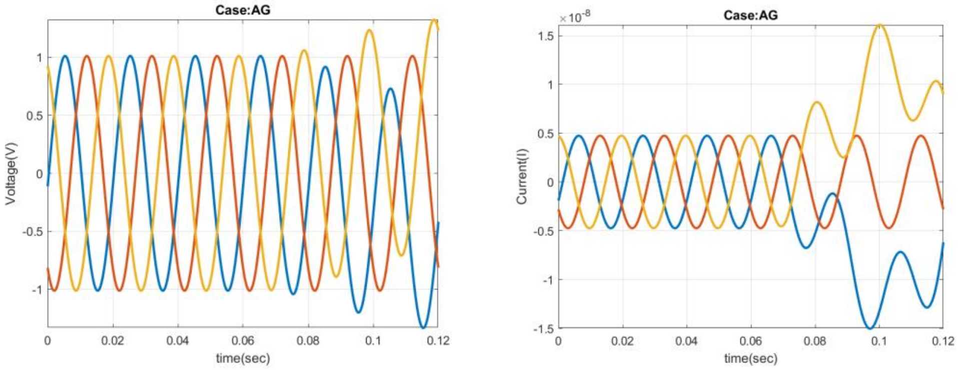

Figure A13: Case-AG

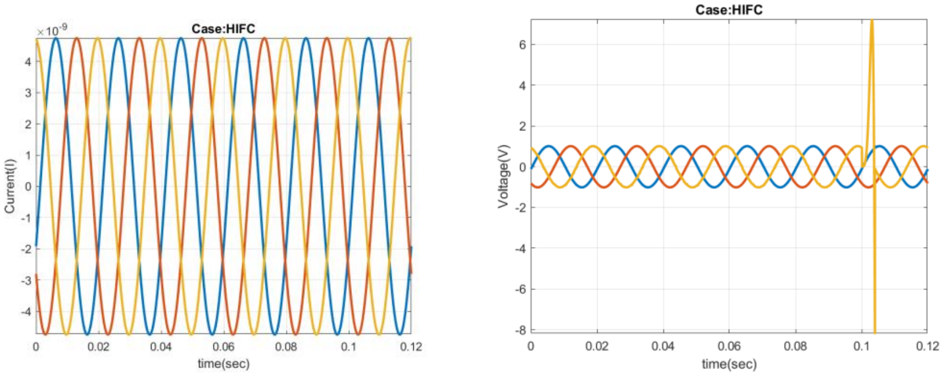

Figure A14: Case-HIFC