Received: 4 January 2024 | Revised: 1 April 2024 | Accepted: 6 May 2024
DOI: 10.1049/gtd2.13186

IET Generation, Transmission & Distribution
The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH

A customised artificial neural network for power distribution system fault detection

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Abstract

Machine learned fault detection approaches are being increasingly used for fault detection in distribution grid. However, the performance of the models can be improved by customizing the models. In this regard, a customised artificial neural network (CANN) for fault detection in a distribution grid is proposed in this paper. The proposed work develops a CANN that combines the "up-pyramid" and "down-pyramid" model of ANN into a "custom-pyramid" model. As a result, the same model can be used both for determining the types of fault as well as its location. The data needed to train the model has been taken from a reconfigured IEEE-33 bus distribution system developed in Typhoon HIL real-time simulator. Spectral-kurtosis is utilized for extraction of features of the faulted transient signals which are used as input data to develop the CANN. The result showcases that the reduction of input features reduces computational complexity without compromising its accuracy. The proposed model classifies fault location with an accuracy of 95.43%. The proposed method also identifies fault type with an accuracy of 96.08%. Several test cases have been developed to test the method. The method proved to be able to perform in most of the cases.

1 | INTRODUCTION

The tech-based society is now being increasingly dependent on electricity and its related applications. Almost all the equipment in the households are run with electricity which simplifies the task and aids in saving time in our busy lives. Thus, electricity has become an integral part of human life. This has triggered a competitive environment among the electrical power providers in terms of continuity and reliability of power service [1]. For this, the power operators need to avoid power system faults and its related outages as quickly as possible to decrease the impact on the consumers [2].

Fault occurs in a distribution system when any two phases or all the phases of the distribution line come in contact with each other either solidly or through physical structures like branch of trees, birds, etc. When it occurs, there is a deviation from the normal operating conditions of the distribution grid. Out of these faults, some faults are short lived and normal conditions are retrieved after a short time interval. These faults, termed as temporary faults, do not possess problems in general [3]. However, some faults are permanent and are not cleared automatically. Disruptions of the distribution line leading to physical contact with the earth, insulation failure of the power cables, sagging, etc., are some of the permanent faults. These faults need to be recognized and removed by the power protection engineers as soon as possible to maintain the power reliability. Out of all the power system outages instants, faults contribute almost three-fourth of it [4].

1.1 | Impetus of the research

The traditional distribution system had a smaller geographical span. The components used in it were simple and managing the power flow was easier due to its unidirectional nature [5]. Hence, any occurrence of fault did not exhibit a major problem as they were easier to detect as well as locate. The fault could be easily located by conventional approaches such as trial and error switching, manual inspection, etc. Even the protection equipment in some advanced distribution grids had a simple algorithm for fault detection and had a very minimal chance of nuisance tripping. As technology progressed, the distribution system got increasingly complexed. The economical as well as population growth also led to an expand in the geographical extent of the distribution power system. The modern distribution system paradigm has a bidirectional power flow due to the penetration of distributed energy resources triggered by the introduction of various national and international policies such as sustainable development goal 7 [6]. Thus, owing to the increase in geographical sprawl and intricacies of the distribution system, the traditional fault detection approaches will not work. Hence, all the protection algorithms and devices need to be upgraded to ensure power continuity to the modern consumers.

The modern distribution grid is equipped with advanced meters such as phasor measurement units, smart meters, etc [7]. These instruments measure and record data at a high accuracy and in high volume. These high voluminous data can cater to the need of developing an algorithm for fault detection in a complex distribution grid. Embracing the era of artificial intelligence, a customised machine learned (ML) fault detection approach can be developed to detect and classify faults in power distribution system.

1.2 | Previously published papers related to fault detection

The previously published work on fault detection technologies can be categorised into two divisions—traditional and modern methods. The traditional methods deal with simple approaches such as impedance calculation, travelling waves, etc. The modern methods can further be divided into phasor measurement units-based methods, signal processing methods, knowledge-based methods and ML based methods. The basic principle of working and the different variations of each technique is explained in the subsequent sections.

1.2.1 | Traditional methods

The travelling wave technique uses the principle of transmission and reflection of travelling waves in between the line terminal and location of the fault. For an uniterminal network, the velocity and time of the travelling wave are calculated for estimating the fault location in [8]. For a biterminal network, a real time fault location is estimated based on travelling wave and a communication system [9]. In impedance-based techniques, the impedance between the fault location and a specific measurement location is calculated for estimation of faults. In [10], the imaginary portion of the impedance is compared against the reactance of the line for detecting faults. In [11], a direct method is presented which utilizes the admittance matrix, fault admittance matrix and the load impedance matrix for estimation of faults. The conventional methods are simple but suffers inadequate classification ability and slower detection time for complex distribution systems.

1.2.2 | Modern methods

The phasor measurement units-based technique employs synchrophasors for detecting fault at various locations by exploiting the current and voltage phasors obtained from the phasor measurement units. The Thevenin equivalent of zero sequence, positive sequence and negative sequence for different source types is calculated in [12] from the synchrophasor data to detect fault. The difference in magnitude of the change of voltage phase angle with time between the fault location and point of common coupling of a microgrid is estimated with phasor measurement units and is used for fault detection in [13]. These methods have an advantage of high accuracy but have huge capital costs. Besides, these methods rely on communication channel and reference phasors which may get disrupted during catastrophize or cyber-attack.

The last few decades witnessed the growth in use of signal processing techniques and pattern recognition methods in the field of fault detection. The methodology behind these techniques involve measuring the fault related signals such as voltage, current, etc. and analysing the signals with advanced signal processing methods for obtaining some features or for a clear representation of signals. A fault detection method based on cumulative sum of wavelet transform features is explained in [14]. In [15], the authors have processed voltages obtained with micro phasor measurement units with Fortescue transform to obtain the sequence component angle. The angular sum of the positive and negative sequence components is assessed and the highest value is used for detection of island and fault events. A Stockwell transform based differential fault detection and classification approach is dealt in [16]. PSCAD and MATLAB software is used to simulate fault conditions in IEEE 14 bus system and WSCC 9 bus system and to develop a Hilbert Hwang transform based fault detection methodology in [17]. Mathematical morphology-based fault detection method is presented in [18]. These methods are helpful to visualize the fault signals in a better way. However, determination of the thresholds for classification of the faults become difficult for large systems.

The last few years have seen a rapid increase in the computing power of the machines. This has led to an increase in the usage of computer aided knowledge-based methods of fault detection. The most well-known knowledge-based method is the fuzzy logic method which employs the idea of possibility in stead of probability. The higher order statistics are developed in [19] to probe the fault signal characteristics for classifying by using fuzzy logic. The line currents of all the phases are measured in [20] and are analysed with fuzzy logic for the determination of type of fault. [21] is an extended version of [20] where unbalanced network is considered for fault classification. An automated program flow and control methodology with the application of fuzzy logic for classification of faults is presented in [22]. These methods have the advantage of high accuracy but have a disadvantage of huge dependence on the knowledge of an experienced professional.

The shortcomings of the above-mentioned methods have fuelled the usage of ML techniques for detection and classification of different types of faults occurring in power distribution system. These techniques are recently being applied in power system sector in an exponential manner. In these methods, a model is first learned by training it with various input and output features and then it is used to categorise testing data into different categories. The accuracy is then obtained based on the number of instants of correct identification of test data. An artificial neural network (ANN) is trained to aid the operators in identifying faulty section in [23]. In [24], ANN is trained for identifying high impedance faults. The authors in [25] has used a multilayer perceptron neural network for recognizing different faults and its location. Wavelet transform is used along with modular multilayer feed forward neural network for fault identification in [26]. The fundamental components of current and voltage signal are used to train a support vector machine (SVM) in [27] for unhealthy phases for estimating fault location. SVM along with radial basis neural network is used in [28] for identifying fault from voltage signals. A random forest (RF) based fault detection algorithm is achieved within the smart meter in [29]. The angular sum of the zero and positive sequence components of current is assessed and the highest value is used for feeding a trained RF classifier for detecting fault conditions. Wavelet transform with SVM is used in [30] to find fault location. A real time algorithm is developed in [31] that uses mathematical morphology with decision tree (DT) for identification and classification of faults. Instantaneous values of normalised currents of all phases are used in [32] to train a k-nearest neighbour (KNN) classifier for fault detection. The authors in [33] have deployed convolution neural network (CNN) for detection of faults using raw and sampled-data of current and voltages. A real-time hierarchical framework for fault detection, classification, and location in power systems using phasor measurement unit data and deep learning is presented in [34]. A transformer technique with CNN for power fault detection is presented in [35]. The feature extraction is done with CNN and sequence learning is achieved with transformer encoder. After data normalization, an extreme ML technique is employed as the classifier for fault in [36]. A neural architecture search algorithm to optimize deep transformer model for fault detection in electrical power distribution systems is proposed in [37]. The result has a Matthews correlation coefficient of 97.7% for fault location classification. The authors in [38] presented a deep learning-based fault detection method under the condition of imbalanced samples. At first, time-series signals are transformed into an image signal after which an improved conditional variational autoencoder-generative adversarial network is employed for generating fault samples for balancing the training sample set. Fortescue transform with RF algorithm for rapid detection of unintended islanding and faults in distribution generation system is suggested in [39]. The method analyses voltage phasor of zero and negative sequence, calculating angular sum over time to distinguish island and fault scenarios from other disturbance. A histogram-based gradient boost (HGB) algorithm based adaptive fault diagnosis considering hosting capacity amendment in active distribution network is presented in [40]. For the application of ML classifiers in fault detection, generally, the power system researchers ignore the underlying architecture of these ML model. This removes the scope of further improvement in the accuracy of the ML algorithms. Thus, the knowledge of a detailed step by step building of any ML classifier in needed for making room for some possible increase in accuracy.

1.3 | Limitations of previous work and requisites for an improved algorithm

The conventional approaches are simple but possess inadequate classification ability and slower detection time for complex distribution systems. Phasor measurement unit-based methods rely heavily on communication channel and reference phasors which may get disrupted during catastrophize or cyber-attack. For signal processing-based methods, determination of the thresholds for classification of the faults become difficult for large systems. ML based techniques involve applying ML models as a black box rather than analysing the parameters which can have a direct effect on the fault detection algorithm. For example, the performance of an ANN is affected by its architecture. In fact, obtaining the optimum number of hidden layers and their nodes is the biggest challenge in building a network.

Thus, a technique is required which has the capability to detect both fault types as well as fault locations with a single model. This will lessen the computational complexity which is otherwise significant if separate algorithms are used for determining fault types and fault locations. Moreover, the reduction in complexity will aid in minimising the software and hardware cost. It should have a high computational speed when compared with traditional techniques, no problem of threshold settings when compared with signal processing techniques, no requirement of an expert's knowledge when compared with knowledge-based techniques and a common algorithm both for fault types classification as well as fault location estimation when compared with other ML techniques. The present algorithm aims at addressing this above problem. A customised ANN (CANN) model is developed as per the requirement for fault classification and finding its location rather than using an available ANN model as a black box. The data needed to train the model has been taken from a reconfigured IEEE-33 bus distribution system developed in Typhoon HIL real-time simulator [40]. Spectral-kurtosis is utilized for extraction of features of the faulted transient signals which are used to as input data to develop a CANN. The customisation results in an increase of accuracy and a better understanding of the underlying architecture of CANN. The CANN model thus developed can be incorporated in each of the bus in the distribution system as a sensor. On detection of fault, the fault information. That is, the fault type as well as the location, can be sent to the control center for taking the necessary actions.

1.4 | Features of the work

The features of the present work in comparison to other works in the field of fault detection are as follows:

- A CANN model is developed as per the requirement for fault classification and finding its location rather than using an available ANN model as a black box.
- The method of obtaining the optimum number of hidden layers and their nodes of CANN is explained to understand the architecture.
- The method of reducing the input features of CANN to improve the accuracy is stated.
- Real time data are used to train the model to eradicate the errors of simulation data.
- The accuracy of the CANN is higher than the other ML techniques.

1.5 | Organisation of the work

The rest of the paper is organized as follows: Section 2 deals with the test system and a brief detail about the dataset. Section 3 deals with the methodology to develop the CANN where processing and partitioning of the data is explained. The specifications of the customised model and its improvement by reducing the number of input features is also explained in this section. The performance and the results of the CANN is dealt in Section 4. The comparison of the present model with other classifier models is discussed in this section. The last section of the paper concludes the present work.

2 | TEST SYSTEM AND DATASET

The test system consists of an IEEE 33 node distribution test system. The traditional system is modified to transform it into in active distribution network as shown in Figure 1. Three solar distributed generators (DGs) are added to the system, at node 14, 24 and 29. For obtaining results from this network in a real-time stage, "configuration 2" in Typhoon HIL602+ device is taken for maximum utilization of FPGA cores. Several fault types at various locations with various fault resistances are introduced and the high-resolution data obtained from the real-time simulation is logged. The data obtained are voluminous as 2 million samples from the internal signal scope of the simulator is obtained per second. The whole model is explained in detail in [40].

As the fault signals inherently possess a non-stationary character, spectral kurtosis has been executed on the current signals and several features have been derived to study the fault characteristics. The theory of spectral kurtosis and the procedure to obtain the features are explained in detail in [40]. To train and test the proposed ANN, numerous data samples of different transients that appear as faults are analysed, along with the position where these faults occur. A portion of the dataset is shown in Figure 2. The phase current of phase C obtained during the fault is represented by IC. The subdivisions under each phase currents are the value of spectral kurtosis obtained from this signal at different normalised frequency from 0 to 1 with a step of 0.1. Thus, there are ten spectral values corresponding to phase C. FLT represents different fault types and the position column represents the fault locations. Key column represents the class to which the classification of the events belongs. The dataset can be further extended for phase currents of phases A and B. These parts serve as the input matrix for the ML models. As shown by the dataset, there are ten different types of faults that are observed (AB, ABN, AC, etc.). Similarly, the dataset shows that each fault can occur at 28 different possible bus locations in the sampled system. These sections serve as the output matrix for the ML models. Thus, an ANN model is developed that has 30 input features and ten different output classes when classifying fault type and 28 different classes when classifying fault location. A total of 1800 test samples were generated, wherein 80% of the samples were used for training the model and 20% of the data was used for testing the model. The ANN designed to solve fault type and fault location is a custom designed artificial network that takes in the chosen features and makes predictions based on the data it is fed.

One of the limitations of the artificial intelligence-based fault detection methods is data quality. The ensurance of data quality through elimination of bad data and handling missing data is a crucial task. To cater this, the missing data in the dataset is replaced by an average value of neighbouring values. This nullifies the effect of missing data and prevents data skewness. The dataset used in the model takes into account noise, however certain normalization techniques like ignoring very high values and extremely abnormal values are done for a cleaner and more uniform data. Care is taken while tabularizing the data by making equal intervals. The different fault types are also categorized by hot encoding for an accurate dataset. Fault positions are considered for every fault and a uniform dataset is ensured. This is a crucial step which prevents class imbalance which is also reflected in the results.

3 | METHODOLOGY TO DEVELOP THE CANN

3.1 | Model specifications and development

Existing literature proposes no dedicated ML models but uses published models to use it as a classifier. Proposed pyramid neural network is novel as ANN is exclusively customized for classifying faults in an electrical distribution grid. Moreover, wherever neural networks are proposed for fault detection and location determination, they cannot predict both fault type and location together in one model while this proposed model executes both fault type and location together at a very high accuracy. ANN is built on either up pyramid model or down pyramid model. Each model has its own advantages. The present method mainly takes the advantages of both the methods and amalgamates them to obtain a custom pyramid model. In the proposed ANN model, two models were combined to

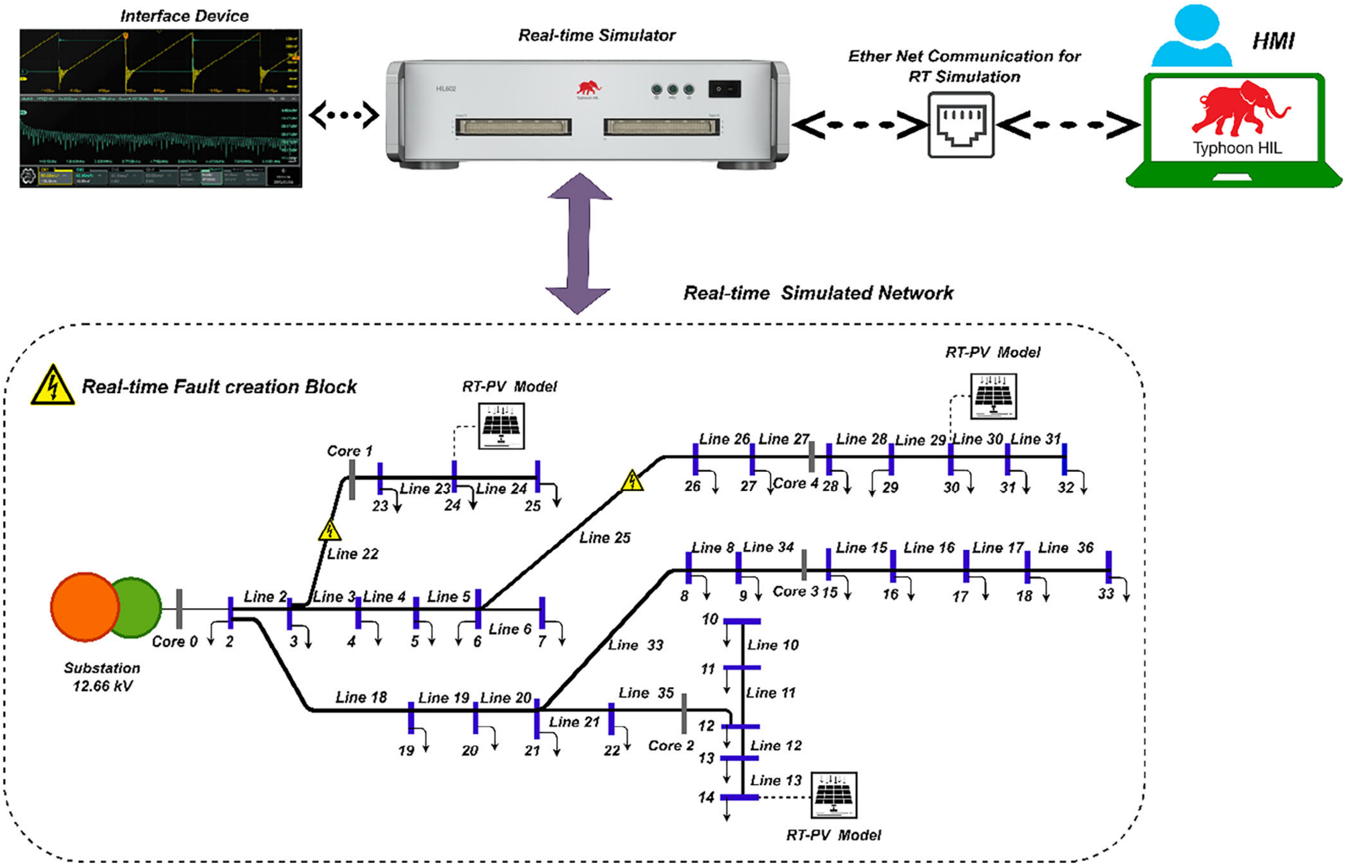

FIGURE 1 Test system considered Human Machine Interface (HMI).

develop a combined ANN architecture as a model to best classify both fault type and fault location. The first model, called the "Up Pyramid," increases the units of the neural network in the order of 32, 128, 512 and 2056 until a final output layer classifies the data. In an ANN, a unit is nothing but a mathematical equation associated with a weight which serves as the most basic building block in a neural network [41]. These increasing layers showed the best experimental results with "Rectified Linear Unit" or "ReLu" activation function whose equation is given as per (1) [42] where x is the input variable. This model performs well with classifying fault location but gives only average results while classifying fault type. To improve model performance to identify fault type, the second model reverses the model layout, starting from the layer with 2056 units and building smaller layers until a final output block. This proposed model is termed as "Down Pyramid" model. This model improves performance on fault type but shows a large drop in accuracy in case of finding fault locations. Thus, to combine the advantages of both models, a third model is built by combining these two models, called the "Custom Pyramid" as shown in Figure 3.

$$ReLU = (0, x)_{\max} \tag{1}$$

The first four layers have been termed as "Up-Pyramid" layers, with increasing units of 32, 128, and 512, respectively. This peaks with a layer called the "Pyramid Peak," which has 2056 units added as a dense layer on top. The layers are now mirrored downwards with units of 512, 128, and 32, which are termed as "Down-Pyramid" layers. The input layer accepts 32 input features corresponding to the 32 features in the dataset while the output layer has 28 or 10 features for classification of fault position or fault type respectively. Thus, the ANN is forming a sequential model on which a final output layer is added with a softmax activation function for multiclass classification as shown in (2) where xi is the input value for the i^{th} vector and xj is the input for the j^{th} vector. In addition to this, dropout layers (0.2) are added to minimise overfitting and improve experimental results [43]. Dropout layers work by randomly selecting 20% of the input layers for training. This percentage was selected through experimentation. The network uses the Adam optimizer with a learning rate of 0.0001 to minimise losses and uses categorical cross entropy, $H(p, q)$, as its loss function as shown in (3) where p is the prediction made by the model and q is the true label.

$$Softmax(xi) = \frac{e^{xi}}{\sum_j e^{xj}} \tag{2}$$

$$H(p, q) = -\sum_{x \in classes} p(x) \log q(x) \tag{3}$$

IC										FLT	Position	Key
0.0292	-0.6047	-0.7745	-0.8991	-0.9613	-0.9104	-0.6953	-0.3047	-0.3443	-0.95	AB	19-20	0
-0.6108	-0.5967	-0.6108	-0.7665	-0.7524	-0.7335	-0.8467	-0.9505	-0.5825	0.6344	ABC	19-20	0
1037.9	-1.3	2.1	2.1	97.2	-1.3	-1.3	-1.3	-1.3	1547.4	ABN	19-20	0
-0.6156	-0.6495	-0.6807	-0.7995	-0.7571	-0.7542	-0.8448	-0.8703	-0.5675	-0.208	AC	19-20	0
-0.623	-0.6796	-0.7113	-0.7838	-0.7521	-0.743	-0.8811	-0.9558	-0.5777	-0.7045	ACN	19-20	0
-0.466	-0.6472	-0.734	-0.8321	-0.7981	-0.7679	-0.9226	-0.7906	-0.4925	-0.9264	AN	19-20	0
-0.6213	-0.7085	-0.7058	-0.7957	-0.756	-0.7375	-0.8723	-0.8617	-0.587	-0.3096	BC	19-20	0
-0.623	-0.6706	-0.7385	-0.7521	-0.7521	-0.7611	-0.8494	-0.9219	-0.5777	-0.5777	BCN	19-20	0
1465.8	29.2	63.2	22.5	1530.4	104	36	70	416.4	1540.6	BN	19-20	0
-0.6451	-0.69	-0.7058	-0.7877	-0.7534	-0.7323	-0.904	-0.8591	-0.5817	-0.336	CN	19-20	0
-0.6909	-0.6819	-0.7136	-0.786	-0.7317	-0.7068	-0.854	-0.8585	-0.5709	-0.9423	AB	19-20	0
-0.6396	-0.6245	-0.6698	-0.8094	-0.7566	-0.7189	-0.9	-0.7981	-0.5679	-0.6962	ABC	19-20	0
1292.6	-1.3	-1.3	-1.3	593	-1.3	-1.3	-1.3	5.5	1547.4	ABN	19-20	0
-0.6266	-0.6213	-0.6821	-0.7772	-0.7587	-0.7402	-0.9092	-0.8696	-0.5923	-0.8908	AC	19-20	0
-0.6184	-0.6712	-0.7108	-0.7901	-0.7571	-0.7175	-0.8363	-0.7835	-0.5986	-0.5127	ACN	19-20	0
-0.6524	-0.5901	-0.6665	-0.7939	-0.7514	-0.7458	-0.8307	-0.8731	-0.5816	-0.9241	AN	19-20	0
-0.5906	-0.6358	-0.6811	-0.8283	-0.7604	-0.7151	-0.8736	-0.8283	-0.5906	-0.3302	BC	19-20	0
-0.6358	-0.6698	-0.6811	-0.8057	-0.7604	-0.7038	-0.8623	-0.8057	-0.5792	-0.6698	BCN	19-20	0
1126.2	-1.3	-1.3	-1.3	1340.2	-1.3	-1.3	-1.3	12.3	1547.4	BN	19-20	0
-0.6566	-0.6264	-0.717	-0.7774	-0.7774	-0.6566	-0.8981	-0.6868	-0.5358	-0.6264	CN	19-20	0
-0.6742	-0.6187	-0.7138	-0.793	-0.7481	-0.7111	-0.8617	-0.8485	-0.5553	-0.9172	AB	19-20	0
-0.6198	-0.6198	-0.6726	-0.8179	-0.7651	-0.6462	-0.8708	-0.8311	-0.567	-0.7915	ABC	19-20	0
1221.3	-1.3	-1.3	-1.3	518.3	-1.3	-1.3	-1.3	5.5	1547.4	ABN	19-20	0
-0.6127	-0.6608	-0.709	-0.7995	-0.7599	-0.7344	-0.8929	-0.8901	-0.5759	-0.9269	AC	19-20	0
-0.6132	-0.6396	-0.6925	-0.7981	-0.7717	-0.6396	-0.9038	-0.8245	-0.5604	-0.5868	ACN	19-20	0
-0.6524	-0.6608	-0.7203	-0.791	-0.7571	-0.7429	-0.9099	-0.8476	-0.5816	-0.9184	AN	19-20	0
-0.6604	-0.6226	-0.6981	-0.8113	-0.7736	-0.5472	-0.8868	-0.8491	-0.5094	-0.3585	BC	19-20	0
-0.6085	-0.6745	-0.6745	-0.8066	-0.7406	-0.6085	-0.7406	-0.8066	-0.5425	-0.6745	BCN	19-20	0
1058.3	-1.3	-1.3	-1.3	1306.2	-1.3	-1.3	-1.3	8.9	1544	BN	19-20	0
-0.6887	-0.6887	-0.6887	-0.6887	-0.6887	-0.0283	-0.8208	-0.8208	-0.5566	-0.6887	CN	19-20	0
-0.6477	-0.6292	-0.6662	-0.7904	-0.756	-0.7138	-0.8723	-0.8485	-0.5711	-0.9013	AB	19-20	0
-0.5962	-0.6264	-0.6868	-0.7774	-0.7472	-0.3547	-0.8679	-0.8377	-0.566	-0.7472	ABC	19-20	0
1139.8	-1.3	-1.3	-1.3	470.8	-1.3	-1.3	-1.3	5.5	1547.4	ABN	19-20	0
-0.6425	-0.6538	-0.6877	-0.8009	-0.7613	-0.7047	-0.8972	-0.8066	-0.5575	-0.9311	AC	19-20	0
-0.6604	-0.5849	-0.7358	-0.7358	-0.8113	-0.283	-0.8868	-0.8113	-0.5094	-0.2075	ACN	19-20	0
-0.6382	-0.6269	-0.6467	-0.7882	-0.7542	-0.7458	-0.8448	-0.8476	-0.5618	-0.8958	AN	19-20	0
-0.6132	-0.6132	-0.7075	-0.8019	-0.8019	-0.0472	-0.8019	-0.8019	-0.5189	-0.3302	BC	19-20	0
-0.6132	-0.6132	-0.5189	-0.8019	-0.8019	-0.2358	-0.8962	-0.8019	-0.6132	-0.4245	BCN	19-20	0
827.4	-1.3	-1.3	-1.3	1279.1	-1.3	-1.3	-1.3	12.3	1547.4	BN	19-20	0
-0.566	-0.9434	-0.566	-0.9434	-0.566	2.0755	-0.566	-0.566	-0.566	-0.1887	CN	19-20	0
-0.6372	-0.5923	-0.6636	-0.8089	-0.7534	-0.7243	-0.8538	-0.8485	-0.5474	-0.9304	AB	19-20	0
-0.6274	-0.6274	-0.7123	-0.7123	-0.7972	0.2217	-0.7972	-0.7972	-0.5425	-0.7123	ABC	19-20	0
1126.2	-1.3	-1.3	-1.3	447	-1.3	-1.3	-1.3	5.5	1547.4	ABN	19-20	0
-0.6066	-0.6198	-0.6726	-0.8047	-0.7519	-0.6462	-0.884	-0.8311	-0.5538	-0.9236	AC	19-20	0
-0.5755	-0.7453	-0.7453	-0.9151	-0.7453	0.2736	-0.9151	-0.7453	-0.4057	-0.4057	ACN	19-20	0
-0.6134	-0.6768	-0.6847	-0.7666	-0.7587	-0.7534	-0.9198	-0.8062	-0.5421	-0.8775	AN	19-20	0
-0.5755	-0.7453	-0.7453	-0.7453	-0.7453	0.9528	-0.7453	-0.7453	-0.4057	-0.066	BC	19-20	0
-0.5755	-0.7453	-0.7453	-0.7453	-0.7453	0.4434	-0.7453	-0.9151	-0.5755	-0.4057	BCN	19-20	0

FIGURE 2 A portion of the dataset.

The computational complexity of the CANN is directly dependent on the number of epochs. Hence, to find the optimal number of epochs, the model is trained up to 1300 epochs and its accuracy curves are plotted in Figure 4, with losses plotted at every 50 epochs to better illustrate the decrease in loss over epoch time. It can be seen from the figure that near 1000 epochs, the accuracies remain almost constant. Thus, 1000 epochs are considered for the proposed CANN. The complete specifications of the architecture of this model is given in Table 1. The first column represents layer name, the second represents the shape of the input that the layer is designed to process while the third column represents the number of

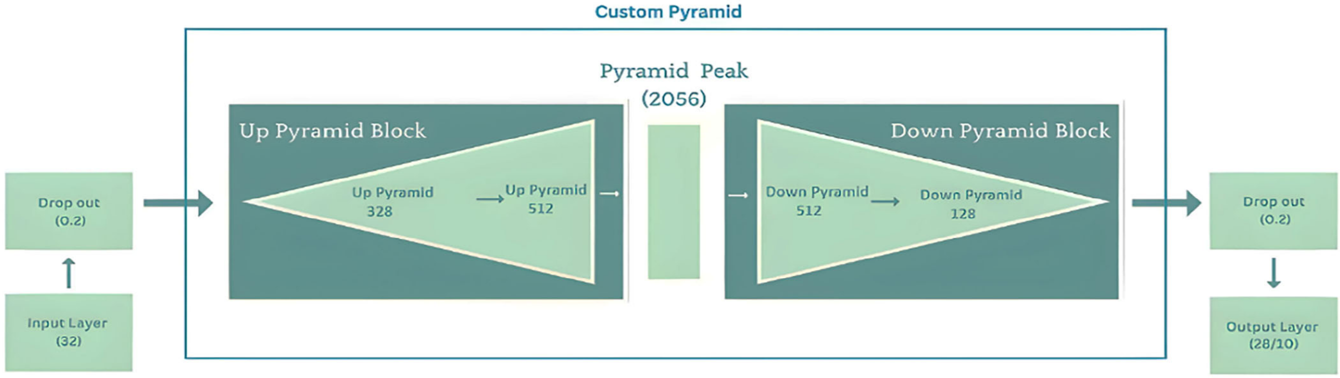

FIGURE 3 CANN architecture.

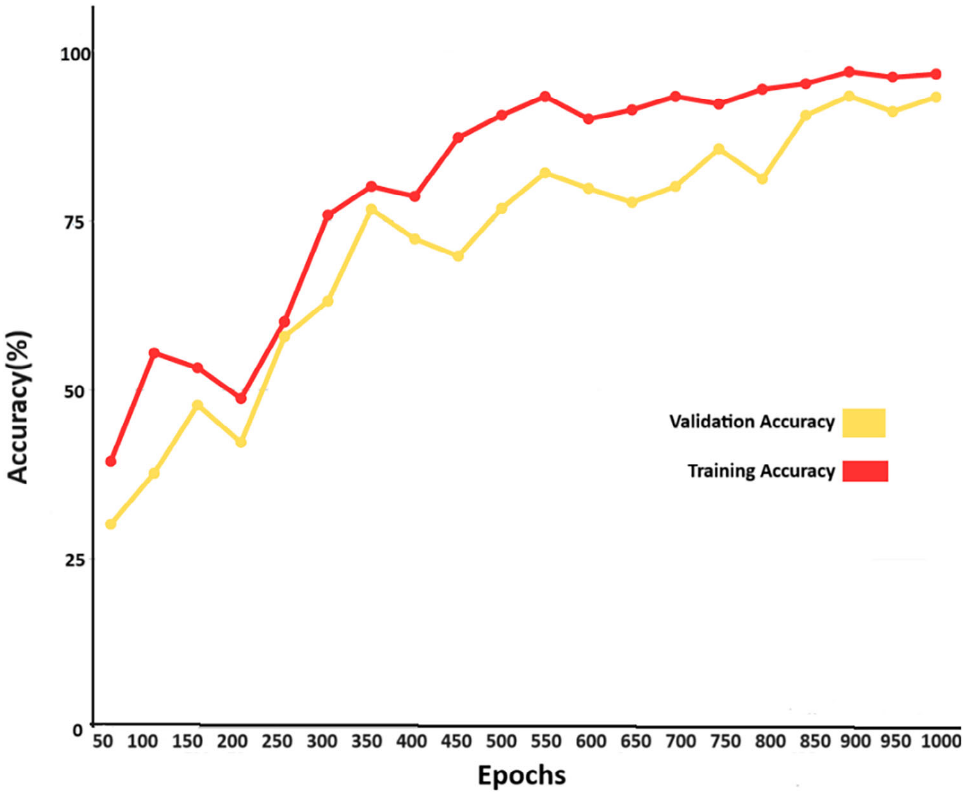

FIGURE 4 Variation of accuracy with number of epochs.

parameters which are calculated by the model itself over a training epoch. A comparison of the performance of all three pyramid models is given in Figure 5 which shows that the customised pyramid ANN architecture works better than the up-pyramid as well as the down-pyramid ANN architecture both for fault types as well as fault locations.

3.2 | Improving model efficiency by reducing features

The computational complexity is also directly dependent on the number of input features. It is always advisable to reduce the number of features without compromising the performance of a ML model. To achieve this, accuracy is obtained considering all the input features except one at a time and the accuracy is plotted in Figure 6. For example, the accuracy corresponding to IA0 in the x-axis represents the accuracy obtained by the classifier without considering IA0. A similar explanation follows for other features. The corresponding features which reduces the accuracy when not considered are the most important input parameters. After several trial and error, a threshold accuracy of 90% is set as shown in the figure. As a result, the number of features was reduced from the original number of 30 to 15 most important features. Hence, as seen in Figure 6, the features IA2, IA4, IA5, IA7, IB2, IB3, IB6, IB7, IB9, IC0, IC1, IC5, IC6, IC7, IC9 are the important features selected for the network.

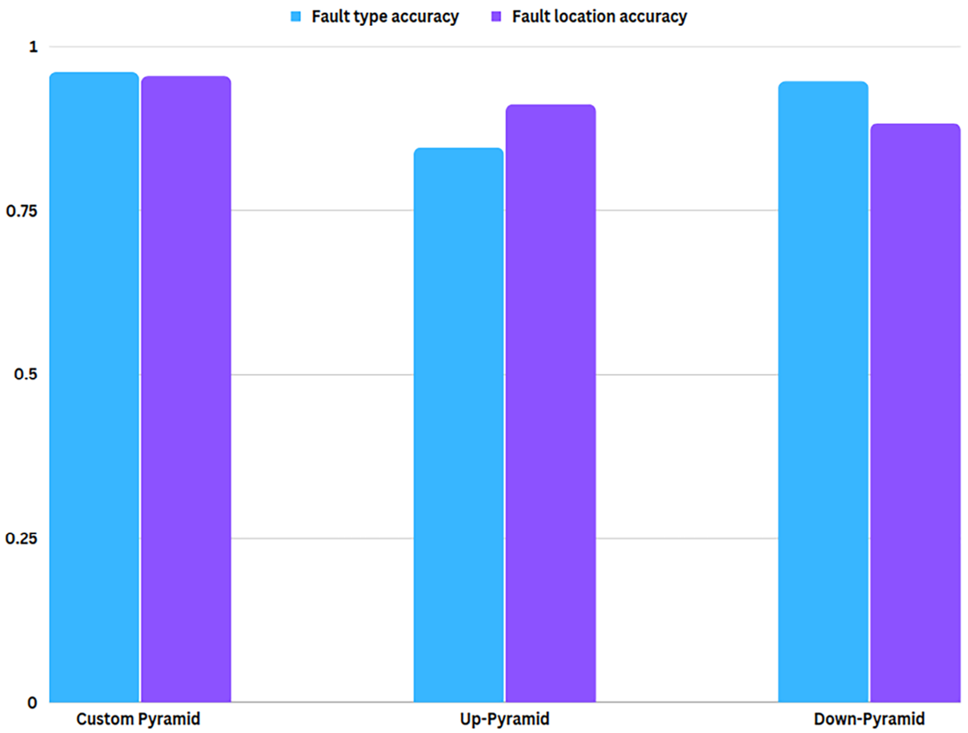

FIGURE 5 Comparison of the performance of all three pyramid models.

TABLE 1 Specifications of the architecture of the CANN.

Layer (type)	Output shape	Parameters
Input_layer	(None, 32)	992
dropout (Dropout)	(None, 32)	0
Up-Pyramid1	(None, 128)	4224
dropout_1 (Dropout)	(None, 128)	0
Up-Pyramid2	(None, 512)	66048
dropout_2 (Dropout)	(None, 512)	0
Pyramid-Peak	(None, 2056)	1054728
dropout_3 (Dropout)	(None, 2056)	0
Down-Pyramid2	(None, 512)	1053184
dropout_4 (Dropout)	(None, 512)	0
Down-Pyramid1	(None, 128)	65664
dropout_5 (Dropout)	(None, 128)	0
output_layer	(None, 30)	3870

4 | PERFORMANCE AND RESULTS

4.1 | Fault type classification

The accuracy of the CANN is first compared with various classical ML models for the classification of fault types. Logistical regression (LR) gives an accuracy of 45.45%, KNN performs classification with 75.401% accuracy, SVM classifies with 51.06% accuracy, DT with 83.16% accuracy, Naïve Bayes (NB) with 52.38% accuracy and RF classifies different fault types with an accuracy of 93.04%. The CANN outperforms these standard ML models by classifying fault types with an accuracy of 96.03%. Figure 7 displays how the CANN has very high classification accuracy and compares classification metrics of precision, recall, and F1 score with other classifiers as per (4)–(6), where $\overset{\vee}{t}$ = true positives, $\tilde{t}$ = false positives, $\overset{\vee}{n}$ = true negatives and $\tilde{n}$ = false negatives [44, 45]. Table 2 shows how the CANN can classify each fault, with single-line to ground faults being accurately identified with the highest accuracy that is, the model performed efficiently in classifying BN, and CN faults, while it performed most poorly on BC, ABC and BCN faults. Upon testing the proposed model on the test set it was seen that classification accuracy of 96.03% is observed as indicated by the confusion matrix in Figure 8. The confusion matrix allows visualization of tested data where the predictions are on the vertical axis while the ground truth is on the horizontal axis.

$$Precision = \check{t}/\tilde{t} + \check{t} \tag{4}$$

$$Recall = \check{t}/\tilde{n} + \check{t} \tag{5}$$

$$F1\ score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{6}$$

4.2 | Fault positions classification

The dataset is tested using traditional ML algorithms. Out of these, LR can classify fault positions with an accuracy of 30.75%. KNN identifies position with an accuracy of 64.17%, SVM performs with 31.55% accuracy and NB classifies position

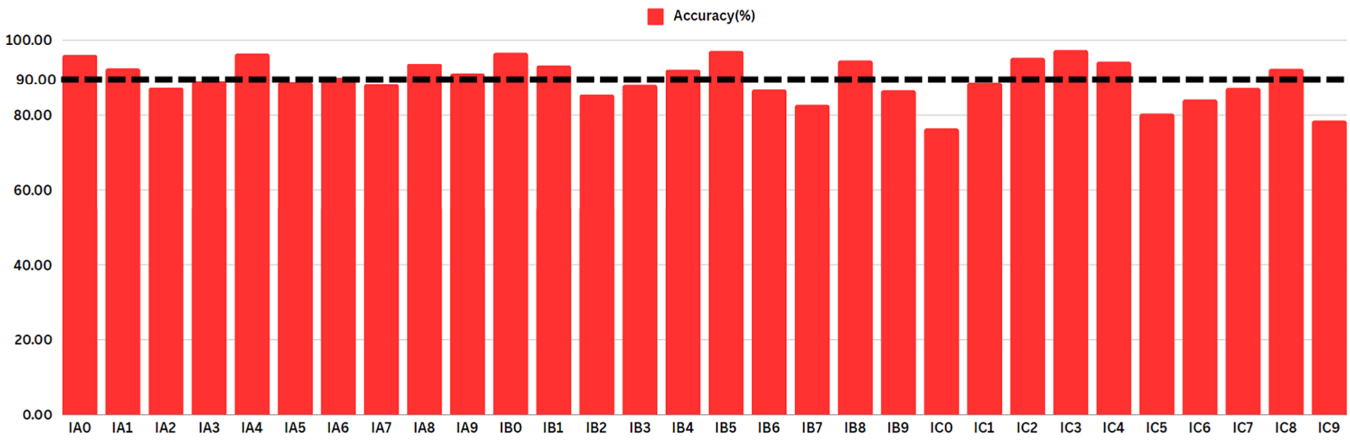

FIGURE 6 Reduction of features.

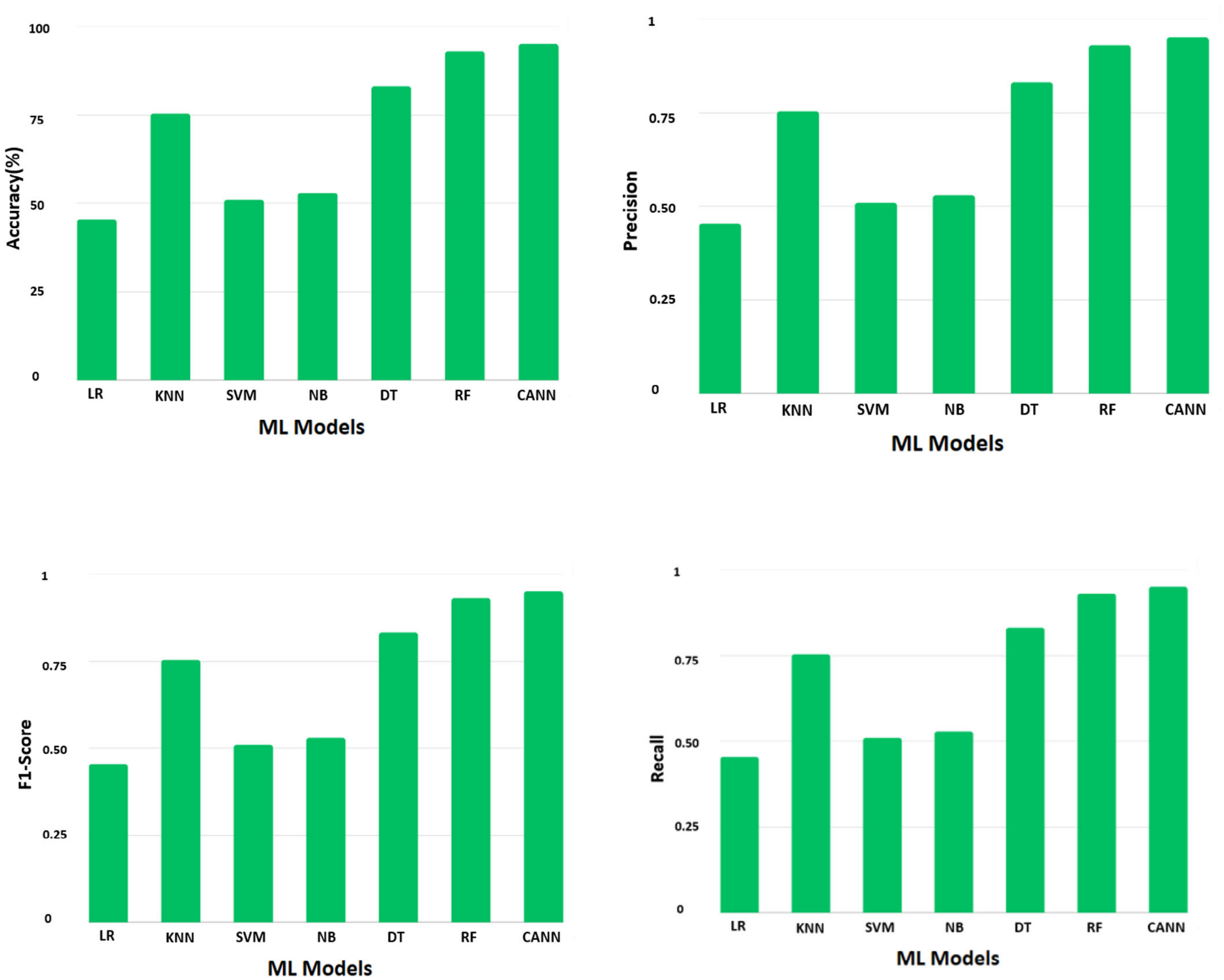

FIGURE 7 Comparison of CANN with other ML methods for fault type classification.

TABLE 2 Performance of CANN for fault type classification.

Fault type	Precision	Recall	F1 score
AB	0.96	0.99	0.98
ABC	0.95	0.92	0.94
ABN	0.98	0.98	0.98
AC	0.97	0.98	0.98
ACN	1	0.98	0.99
AN	0.98	0.95	0.96
BC	0.93	0.95	0.94
BCN	0.95	0.92	0.94
BN	0.99	0.99	0.99
CN	0.99	0.99	0.99

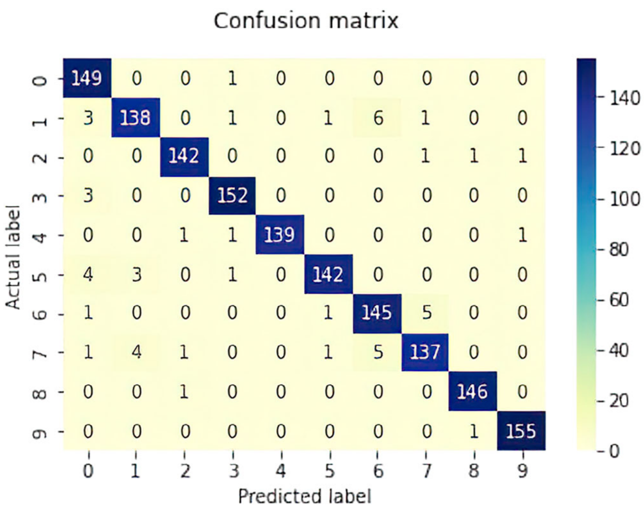

FIGURE 8 Confusion matrix for fault type classification.

at 47.05% accuracy. DT with and RF performs slightly better, categorising simulated data with accuracies of 67.647% and 81.01%, respectively. The dataset is now tested on the CANN. The CANN classifies fault positions with a significantly higher accuracy of 95.43%, and its accuracy at each fault position is shown in Table 3. It can be seen from the table that the method works best for fault between bus 19–20, 20–21 and13–14 and worst for bus 11–12. Figure 9 shows a comparison between the CANN and standard ML models where the classification metrics of precision, recall, and F1 score with other classifiers are calculated as per (4)–(6). The model is tested on a similar test set where samples are shuffled to prevent overfitting. It is observed that the model still performs at accuracies of over 95%, which are given in Figure 10 as its confusion matrix, which establishes its high efficiency in identifying fault positions.

4.3 | Results for different out of the box scenarios

The proposed model is tested against some out of the sample dataset that is, the conditions that are not considered in the training or testing data. For this, several types of faults at different locations is simulated with different fault inception angle and fault resistances and the results are tabulated in Table 4. It can be seen that the proposed algorithm works perfectly for all cases except the cases for high impedance fault that is when the fault resistance exceeds 200 Ω and when the fault inference angle exceeds 330°. For further analysing the model, several scenarios are simulated considering Gaussian noise at various levels. The results for different noise levels in dB is shown in Table 5. It can be seen from the table that the method is able to classify the faults and its locations up to 30 dB of noise. The variation of the accuracy with noise both for fault type as well as fault location is shown in Figures 11 and 12, respectively. It can be observed that for both the cases, the algorithm performs satisfactorily up to 30 dB of noise after which the accuracy decreases. For fault types classification, the decrease in accuracy with increase in noise level is lesser than that of fault location.

TABLE 3 Performance of CANN for fault location classification.

From–To	Precision	Recall	F1 score
19–20	0.97	1	0.98
20–21	1	0.93	0.97
27–28	0.88	0.95	0.91
29–30	0.93	0.85	0.89
28–29	0.83	0.98	0.9
26–27	0.9	0.92	0.91
15–16	0.9	0.91	0.9
8–9	0.93	0.91	0.92
21–8	0.94	0.9	0.92
13–14	0.98	1	0.99
7–26	0.94	0.96	0.95
6–7	0.98	0.93	0.95
5–6	0.92	0.94	0.93
4–5	0.89	0.91	0.9
3–4	0.98	0.92	0.95
0–2	0.96	0.96	0.96
2–3	0.89	0.93	0.91
24–25	0.95	0.93	0.94
23–24	0.96	0.92	0.94
3–23	0.98	0.96	0.86
18–33	0.91	0.92	0.92
17–18	0.98	0.92	0.95
16–17	0.89	0.85	0.87
12–13	1	0.98	0.99
11–12	0.92	0.69	0.79
10–11	0.81	0.85	0.83
22–12	0.94	0.96	0.95
21–22	0.96	0.94	0.95

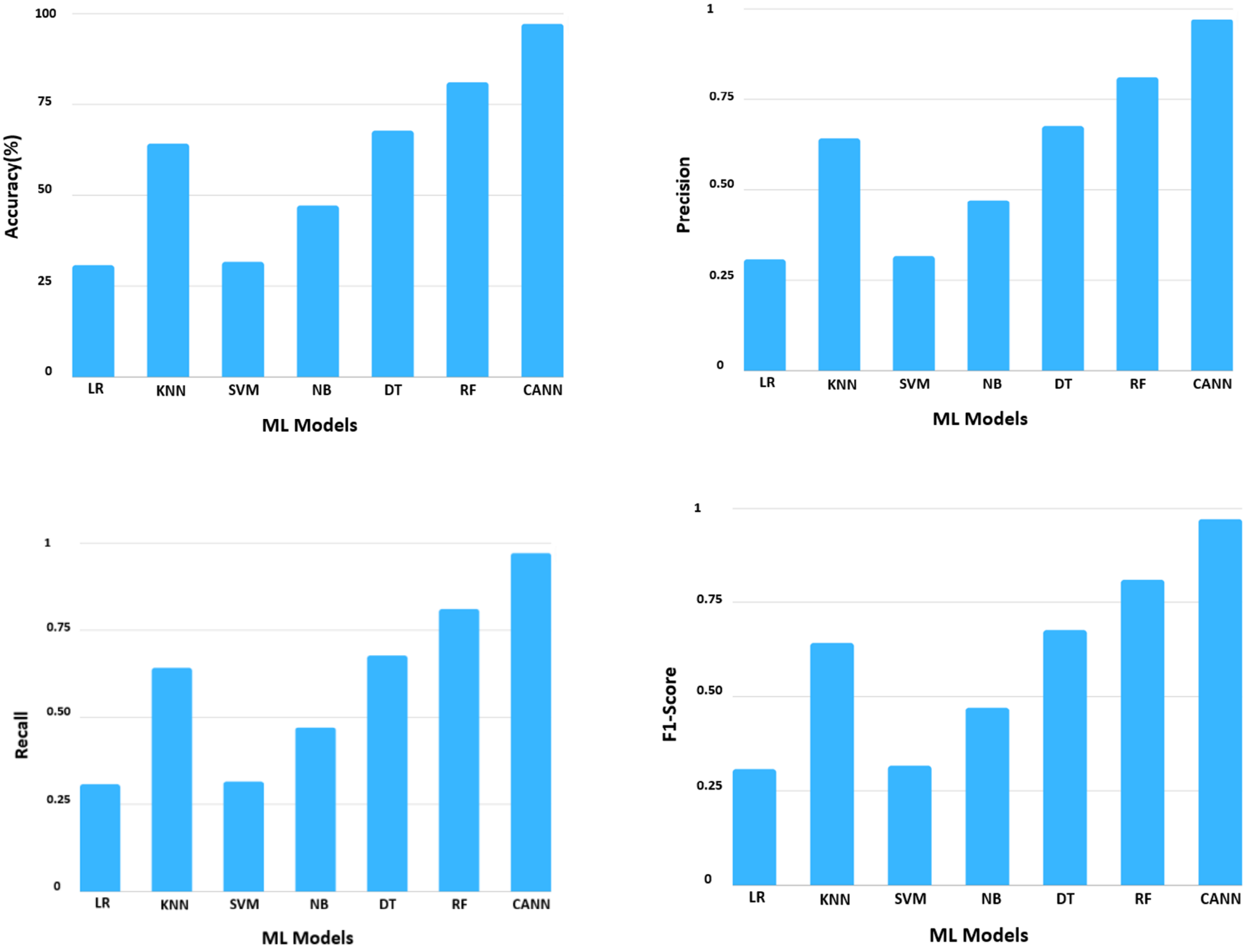

FIGURE 9 Comparison of CANN with other ML methods for fault location classification.

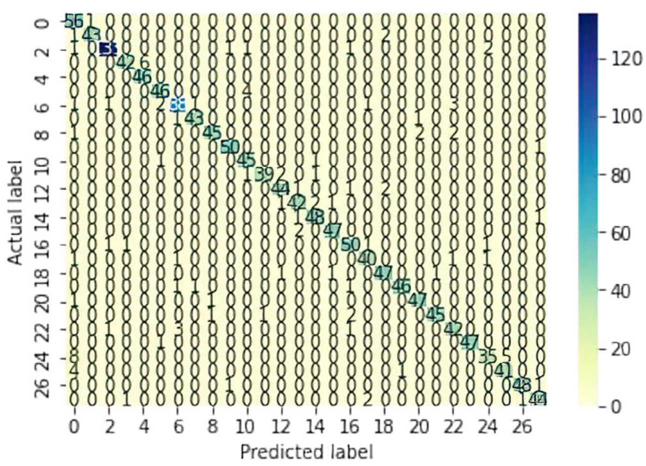

FIGURE 10 Confusion matrix for fault location classification.

4.4 | Results for another dataset

The proposed model is tested on other microgrid situations such as for vehicle-to-grid connection. The microgrid is simulated in a 33 bus microgrid system which is tested against the charging and transport capabilities of electrical vehicles. Various parameters of electrical vehicles are simulated against the system and estimated battery type is predicted using the proposed model. However, its accuracy does not exceed 54% on the tested data while making predictions on fuel usage forecast, while performing at 38.3% for predictions on closest bus, making the proposed CANN model highly application specific.

The presented method is further tested for the same test system as mentioned in Section 2 with underground cable instead of overhead line. The input matrix is generated in the same manner as with overhead line. However, the input matrix is different as the currents are different for overhead line and underground cable due to its constructional features. Moreover, the fault type considered in underground cable are open-circuit fault, short-circuit fault and earth fault. The CANN model thus developed exhibited an overall accuracy of 93.2%.

4.5 | Algorithm time

The execution time of a fault detection technique plays a crucial role. The calculation of the execution time of the proposed technique is as follows:

TABLE 4 Performance of CANN for different fault inference angles and fault resistances.

Description of cases	CANN output for fault type	CANN output for fault location
AB fault between node 6 and 7 with 22 Ω fault resistance and 37° fault inference angle	AB (Correct)	6–7 (Correct)
BCG fault between node 12 and 22 with 68 Ω fault resistance and 72° fault inference angle	BCG (Correct)	22–12 (Correct)
AG fault between node 28 and 29 with 92 Ω fault resistance and 184° fault inference angle	AG (Correct)	28–29 (Correct)
ACG fault between node 11 and 12 with 156 Ω fault resistance and 228° fault inference angle	ACG (Correct)	11–12 (Correct)
BG fault between node 18 and 33 with 187 Ω fault resistance and 339° fault inference angle	AG (Incorrect)	18–33 (Correct)
AB fault between node 23 and 24 with 220 Ω fault resistance and 350° fault inference angle	CG (Incorrect)	3–23 (Incorrect)

TABLE 5 Performance of CANN for different noise levels.

Description of cases	CANN output for fault type	CANN output for fault location
ACG fault between node 15 and 16 with 5 dB noise	ACG (Correct)	15–16 (Correct)
AG fault between node 17 and 18 with 10 dB noise	AG (Correct)	17–18 (Correct)
CG fault between node 26 and 27 with 15 dB noise	CG (Correct)	26–27 (Correct)
ABG fault between node 8 and 21 with 20 dB noise	ABG (Correct)	21–8 (Correct)
BC fault between node 6 and 7 with 30 dB noise	BC (Correct)	7–26 (Incorrect)
BCG fault between node 26 and 27 with 40 dB noise	AB (Incorrect)	27–28 (Incorrect)

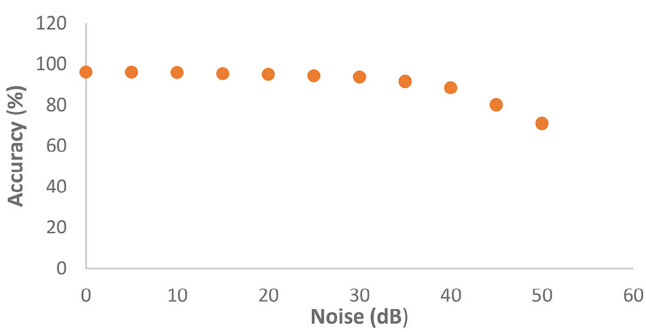

FIGURE 11 Variation of accuracy of fault type classification with noise.

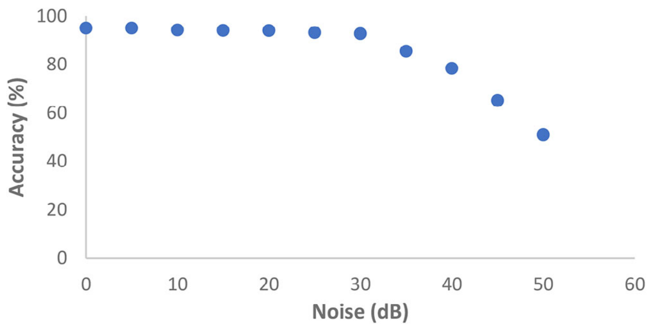

FIGURE 12 Variation of accuracy of fault location classification with noise.

Signal acquisition time (SAT): 10,000 samples are required to obtain the spectral kurtosis. Thus, the signal acquisition time is 10 ms [40].

Processing time (PT): The time required for the execution of spectral kurtosis and CANN on a 4 GB RAM, core i5 processor with clock frequency of 1 GHz is 8 ms.

Time Delay (TD): The communication delay is 5 ms.

Fault Sensing Time (FST): The overall fault sensing time can be evaluated as in (7). Thus, the proposed algorithm has the FST of 23 ms.

$$FST = SAT + PT + TD \tag{7}$$

4.6 | Comparison with other techniques

The greatest advantage of the proposed technique is its ability to detect both fault types as well as fault locations with a single model. This reduces the computational complexity which is other otherwise significant if separate algorithms are used for determining fault types and fault locations. This reduction in complexity will help in reducing the software and hardware cost. It has the advantage of high speed when compared with traditional techniques, no problem of threshold settings when compared with signal processing techniques, no requirement of an expert's knowledge when compared with knowledge-based techniques and a common algorithm both for fault types classification as well as fault location estimation when compared with other ML techniques. The CANN technique has been compared with other techniques in Table 6.

5 | CONCLUSIONS

The occurrence of faults poses a constant threat to the distribution grid operation. The faults occurring in these distribution grids are dangerous and unpredictable. The penetration of renewable-based distributed generators has further complicated the process of these fault detections. Hence, following the aims of Sustainable Development Goal 7, that is, to guarantee access to reliable modern energy for all, a fast and accurate fault detection methodology needs to be developed. In view of this, a CANN for fault detection in a distribution grid is presented in this paper. The data needed to train the model

TABLE 6 Comparison of CANN with other techniques.

Techniques	Advantage	Disadvantage
Traditional	Simple procedure	Slow with limited ability of fault classification
Signal processing	Faults are diagnosed directly	Very difficult to ascertain the thresholds
Knowledge based	Low chances of misclassification	Massively relies on the knowledge of the professional
ML	Less heuristics	No common algorithms both for fault types classification as well as fault location estimation
CANN	Common algorithm both for fault types classification as well as fault location estimation.	Highly application specific

has been collected from a reconfigured IEEE-33 bus distribution system developed in Typhoon HIL real-time simulator. Spectral-kurtosis is utilized for extraction of features of the faulted transient signals which are used as input data to develop a CANN. For better capability of the procedure, optimized feature importance values are considered. The authors have considered other ML techniques to showcase a comparative study with the CANN. The proposed model is also tested in other microgrid situations such as for the vehicle-to-grid system where it performed poorly. The proposed model was hence found to be highly application specific in its usage. Further, the algorithm is tested against various out of sample datasets, such as different fault resistances, fault inference angles, and noise levels. The model gave satisfactory output with some limitations.

There is a considerable scope for improvement in identifying the correct fault position, especially when the fault is between nodes 11 and 12, where accuracy is only at 79%, and while identifying ABC type faults, which are identified only at an accuracy of 94%. Performance of the model can also be improved by the availability of a larger dataset, either by simulation or larger augmented data. Future modification of the model can involve improvement in the classification of selected data cases where the proposed model performs worse than its mean. Due to a lack of data from a real system, the authors are unable to check the effectiveness of the proposed method in a real system, including aerial cable and ground cable. The effectiveness of the proposed method in a real system including aerial cable and ground cable, can be considered as an extended work. Moreover, the impact of DC component on the operation of the proposed method can also be analysed as a future work.

AUTHOR CONTRIBUTIONS

Arnav Bhagwat: Methodology; software; writing—original draft. **Soham Dutta**: Conceptualization; methodology; investigation; writing—original draft. **Vinay Kumar Jadoun**: Conceptualization; methodology. **Sourav Kumar Sahu**: Writing—original draft; writing—review and editing. **Arigela Satya Veerendra**: Investigation; writing—review and editing; supervision.

CONFLICT OF INTEREST STATEMENT

The author declares no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data will be made available on request.

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How to cite this article: Bhagwat, A., Dutta, S., Jadoun, V.K., Veerendra, A.S., Sahu, S.K.: A customised artificial neural network for power distribution system fault detection. IET Gener. Transm. Distrib. 18, 2105–2118 (2024). https://doi.org/10.1049/gtd2.13186