A Dissertation

On

“Soft Computing Techniques for Detection and Classification of Transmission Line Faults”

Submitted in partial fulfillment for the award of the degree

of

MASTER OF TECHNOLOGY

in

ELECTRICAL ENGINEERING

with

specialization in Power System

(Session: 2021-2023)

Submitted By:

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CANDIDATES DECLARATION

I hereby declare that the work presented in the dissertation **"Soft Computing Techniques for Detection and Classification of Transmission Line Faults"** to be accorded the degree of Master of Technology in Electrical Engineering, with specialization in Power System Engineering, submitted to the Department of Electrical Engineering, Assam Engineering College, Jalukbari, Guwahati-13 is an authentic record of my work carried out under the supervision and guidance of Dr. Amrita Ganguly, Professor, Department of Electrical Engineering, Assam Engineering College and under the Co-guidance of Dr. Mridusmita Sharma, Assistant Professor, Department of Electrical Engineering, Assam Engineering College, Guwahati. The matter embodied in this project has not been submitted by me for the award of any other degree.

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CERTIFICATE OF APPROVAL

This is to certify that the project entitled on **"Soft computing Techniques for Detection and Classification of Transmission Line Faults" undertaken** by Mongjam Monika Devi (Roll No PG-E-018), a M. Tech 4^{th} semester student of Electrical Engineering, Assam Engineering College, Guwahati-13 has been carried out by her during the academic year 2022-2023 under my supervision and guidance.

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Date: **External Examiner**

Place:

CERTIFICATE OF ACCEPTANCE

This is to certify that Mongjam Monika Devi (PG-E-018), a M. Tech 4th semester student of the Department of Electrical Engineering of Assam Engineering College has submitted her dissertation on **"Soft computing Techniques for Detection and Classification of Transmission Line Faults"** in partial fulfillment for the award of the degree Master of Technology in Electrical Engineering with specialization in Power System Engineering under Assam Science and Technology University.

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ACKNOWLEDGEMENT

At the very beginning I would like to express my deepest gratitude and sincere thanks to my respected supervisor Dr. Amrita Ganguly, Professor, Department of Electrical Engineering, Assam Engineering College and co-supervisor Dr. Mridusmita Sharma, Assistant Professor, Department of Electrical Engineering, Assam Engineering College for their invaluable supervision, guidance and constructive suggestions throughout the course of my project. I would like to express my deep sense of gratitude to Dr. Aroop Bardalai, Professor and Head of the Department, Department of Electrical Engineering, Assam Engineering College for allowing me to use the facilities of the department.

I would also like to thank all the faculty members of the Department of Electrical Engineering, Assam Engineering College for the free exchange of ideas and helpful discussions.

At last, I would like to thank my loving and dear parents, my sister and brother for their support and interest. A special thanks to the almighty for being there for us always.

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ABSTRACT

In today's era, with the rapid increase in demand of electricity, the number of transmission lines grows progressively. Transmission line are more susceptible to faults as they are exposed to natural environment. These faults need to be immediately solved with less fault clearing time to avoid power outages. To ensure an efficient and reliable power supply to consumers, proper protection of transmission lines is necessary. This requires diagnosis of fault and classification of faults accurately.

Over the years, Artificial Neural Network has attracted global attention. Deep Learning approaches are widely used recently and found to be effective in many power system applications. The main objective of this paper is to diagnose and classify various faults types on transmission lines using different soft computational techniques algorithms namely – ANN (Artificial Neural Network), CNN (Convolution Neural Network) and LSTM (Long Short-Term Memory) and the accuracies of these algorithms are compared. This requires large training dataset and acquisition of real fault data are costly and technically difficult. Furthermore, distinguishing the fault types is complicated due to high data processing requirements.

Therefore, in the first phase of this project a standard 2 bus short transmission Line of length 55km is developed using MATLAB/Simulink. Fault datasets are generated by simulating the Simulink model upon giving different symmetrical and unsymmetrical fault types at different fault locations. ANN is implemented to detect, classify and locate faults. The generated datasets are used to train, test and validate ANN models. The result shows ANN detects faults with very high accuracy, classify faults with an accuracy of 98.3 % and the error given by ANN Locator are very small. In the second phase, a medium transmission line of 105km is considered. Fault dataset are generated using MATLAB/Simulink. Using the generated fault dataset detection and classification is performed by implementing various algorithms such as ANN, CNN and LSTM. It is observed that LSTM performed better with a detection accuracy of 99.9% and classification accuracy of 99.94%.

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CHAPTER 1: INTRODUCTION

1.1 Power System

Electrical power system consists of three major subsystem – a Generation, a Transmission Line and a Distribution system. Generating station or Generation is the source of energy. The electric power is generated in the generating station by 3- Phase alternators operating in parallel. Electric power is usually generated at 11kv however for economic purpose the generation voltage is step up to 132kv using 3-phase transformers. Transmission line system transmits the electric power generated from generation to load centers. And Distribution system distributes the electric power to end users.

Over the years due to the increase in demand of electricity and generation capacity the reserve capacity of transmission line is falling. One solution is to increase the number of transmission lines and improve the reliability. Another alternative is to integrate generation within the distribution thereby reducing the dependance of local loads to transmission grid. This approach is known as Distributed Generation.

Transmission line which is significant portion of electric power system, being exposed to natural are more susceptible to faults. A fault is any electric disturbance, power failure or unusual condition in the power system. The main factor which decreases the efficiency of transmission lines and cause power interruption are faults on the system. These must be cleared as early as possible to restabilize the system. Therefore, fast and accurate identification, separation of the faulty component from remaining of the power system is necessary to minimize the damage to the entire system. Moreover, to ensure a reliable, high quality, uninterrupted power to consumers requires transmission line protection system that is smart, efficient, & robust that can detect, classify transmission line faults.

1.2 Transmission Line and Types of Transmission Line

Transmission lines connects the generating stations and distributing stations. Therefore, interruption in these links disrupts the power flow from generation to end users. Transmission line carry very high voltage from generation to distribution because it offers several advantages such as saving of conductor material and high transmission efficiency. However, there is a limit to which this voltage is increase because increase in transmission voltage may introduce insulation problems, cost of switchgear and transformer equipment is increased. Generally, in India, transmission voltage is carried at 66KV,132KV,220KV and 400 KV.

These transmission lines can be classified based on the location, voltage rating and length. On the basis of location, it is classified as Overhead transmission line and underground transmission lines.

1. Overhead Transmission Line- Overhead lines or overhead transmission lines are the bare conductors supported on poles and towers. In overhead system, the line conductors are hanged in air with the help

of transmission line supports installed at a certain distance. Generally, an overhead line consists of following components –

a. Conductors -which carries electric power from sending end to receiving end.
b. Supports- poles or towers which keeps the conductors at a suitable level above the ground.
c. Insulators- which are attached to supports and insulate the conductors from the ground.
d. Cross Arms – which provide support to the insulators,
e. Miscellaneous items – such as phase plates, danger plates, lightening arrestors and anti-climbing wires.

Overhead Transmission lines can be further classified based on the length of transmission lines-

a. Short Transmission Lines- the length of the transmission line is 50 Km and allowable line voltage limit is below 20 KV.
b. Medium Transmission Lines– the length of transmission line is between 50Km to 150Km and permissible line voltage limit is between 20KV to 100 KV.
c. Long Transmission Lines- the length of transmission line is greater than 150 Km and line voltage limit is above 100 KV.

2. Underground Cables- a typical underground cables consist of one or more conductors with insulation and protective layers. The components require in constructing an underground cable are given below

a. Conductors
b. Conductors Screen
c. Insulation
d. Metallic Sheath
e. Bedding
f. Armoring
g. Serving
h. Bedding

Further, Underground cable can be classified based on their voltage as below-

a. Extra Super Voltage Cables – voltage beyond 132 Kv
b. Extra high-tension cables – voltage between 33kV to 66kV
c. Super tension cables – voltage between 22kv to 33Kv
d. High tension cables -voltage from 1kV to 11kV
e. Low tension cables- voltage up to 1kV

1.3 Transmission line faults

1.3.1 What are faults?

Under normal conditions power system is balanced and it becomes unbalanced on occurrence of faults. A fault can be termed as any certain abnormality in voltage and current in normal power system that represents disturbance in a system. This abnormal condition reduces the insulation strength of conductors which further cause excessive damage to the entire system. Fault occurs at any time and at any location with different magnitude of fault impedance. The point at which a fault occurs is considered as a sink point and as a result the voltage tends to become zero. Thus, all the points those have higher potential than the faulty point start sending current to these faulty points and raise the fault level higher magnitude very higher than that at the normal level.

1.3.2 Types of transmission line faults

Transmission line faults is mainly categorized into two-

1. Open Circuit Faults-The open circuit fault mainly occurs because of the failure of one or two conductors. It is again subcategorized as Open conductor fault, two conductors open fault, three conductors open fault.
2. Short Circuit Faults- Short circuit faults are also called as shunt faults. These faults are caused due to insulation failure between phase conductors or between earth and phase conductors or both. These are the most common and severe kind of faults, resulting in the flow of abnormal high currents through the equipment or transmission lines. If these faults are allowed to persist even for a short period, it leads to the extensive damage to the equipment.

Short circuit fault can be again divided into symmetrical and unsymmetrical faults. The fault which involves all the three phases is known as symmetrical fault. These types of faults remain balanced even after fault. It consists of L-L-Fault (three phase clear earth fault) and L-L-L-G (three phases to earth fault). Whereas unsymmetrical fault gives rise to unsymmetrical current i.e., current having different in magnitude and displacement angle. It consists of L-L fault (two phase fault), L-L-G fault (two phase ground fault), L-G fault (Single phase to Ground fault). The most commonly occurred fault is L-G fault and most severe fault is L-L-L fault. The occurrence of unsymmetrical faults is higher than occurrence of symmetrical fault with a probability of 95-98 %.

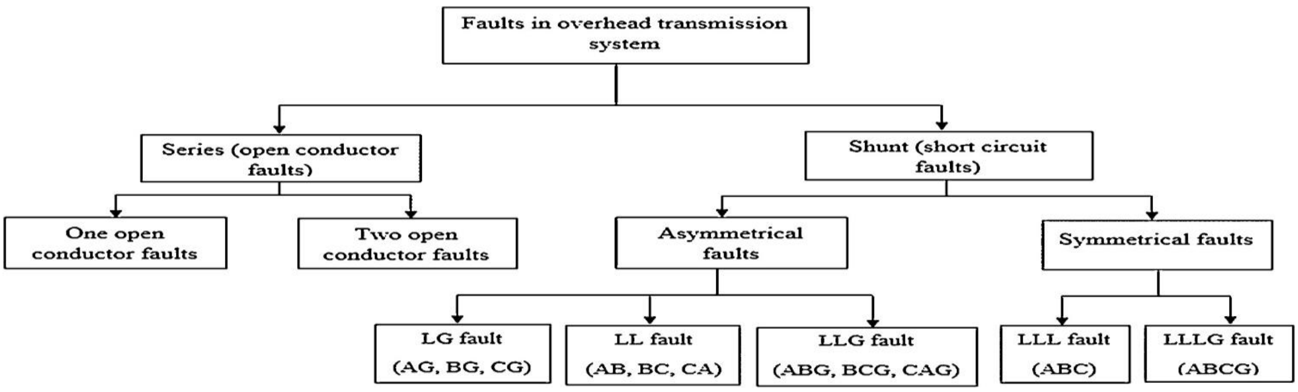

Fig 1. Types of Transmission line faults

1.3.3 Causes of faults

The various causes of transmission line faults are given below-

1. Aircraft and cars hitting lines and structures
2. Birds and animals
3. Contaminated insulators
4. Ice and snow loading
5. Lightening
6. Partial discharges not controlled
7. Punctured or broken insulators
8. Trees
9. Winds etc.

1.4 Protection of Transmission Lines

The expansion of the lines over different terrains and geographic locations makes these most vulnerable to different kinds of atmospheric calamities which more often develops faults in line. It is imperative to remove the faulty line at the earliest to restrict undue outflow of bulk power through the faulted point as well as restore system stability earliest to resume normal power flow operation. Here lays the importance of having a robust fault identification, classification and localization algorithm which would be successfully able to drive as well as actuate the digital relaying system. Researchers have worked out several methodologies in developing improved power system protection algorithms which would be able to serve to eliminate faults immediately on occurrence of the same.

1.5 Objective

- To develop an intelligent Transmission Line protection system, which can detect faults, classify and also identify the location of the faults using ANN.
- To perform detection and classification of different types of transmission line faults using various algorithms such as ANN, CNN and LSTM and compare their accuracies

1.7 Motivation

The project is carried out with the following motivation

- Faults, if not diagnose might result in power outage, energy loss, damage equipment, large scale power quality problems.

- For reliable protection of power systems fast and accurate fault detection is important.
- To ensure continuous and efficient power supply to consumers, protection and maintenance of power transmission line is indispensable.

1.8 Structure of Dissertation

The following dissertation is followed by Literature Review in the Chapter 2. Detection, Classification and Location using ANN in a short transmission line is thoroughly explained in Chapter 3. In the chapter 4, Conventional ANN, CNN, and LSTM methods were employed to carried out Detection and Classification. Chapter 5 is the conclusion section where it gives brief of the work performed and results obtain in this entire project.

CHAPTER 2: LITERATURE RIEVIEW

1. "Power Line Transmission Fault Modeling and Dataset Generation for AI Based Automatic Detection," by authors H. A. Shiddieqy, F. I. Hariadi and T. Adiono. In this paper, considering the difficulty of acquiring real fault dataset, high data processing requirements to distinguish type of fault an IEEE fault model Std C37.114-2004 is considered to generate fault dataset using MATLAB software. The three-phase voltage and current generated from the fault model is used to train AI techniques for automatic detection. Three algorithms were used CNN, DWT+CNN, and DWTenergy+ANN [1].

2. "Deep Learning Approach for Transmission Line Fault Classification," by M. A. M. Nasrin, A. M. S. Omar, S. S. M. Ramli, A. R. Ahmad, N. F. Jamaludin and M. K. Osman. The study has employed DNN based approach for time series classification of transmission line faults which has the capability to automatically discover and extract features. Its experimental findings shows that time data series approach improves the classification accuracy from other baseline techniques. Fault voltage and current were considered the main parameter for classification. DNN gives very high accuracy of classification [2].

3. "Convolutional Neural Network Based Fault Detection for Transmission Line," by A. Bhuyan, B. K. Panigrahi, K. Pal and S. Pati. A deep learning-based technique, CNN is implemented to detect different types of symmetrical and unsymmetrical faults. Phase current time graph images of a proposed system is generated using MATLAB/ Simulink. These images are fed as input to CNN for training and testing purposes using Python Programming language [3].

4. "Intelligent Relay Based on Artificial Neural Networks ANN for Transmission Line," R. Alilouch and F. Slaoui-Hasnaoui. In this paper, feed forward-back propagation Artificial Neural Network is employed in a numerical relay. ANN is trained using measured fault voltages and currents to detect, classify and locate faults. A detail analysis of ANN performance is performed by changing the number of hidden layers to obtain optimal results [4].

5. "ANN Based Fault Detection & Classification in Power System Transmission line," by the authors M. R. Bishal, S. Ahmed, N. M. Molla, K. M. Mamun, A. Rahman and M. A. A. Hysam. In this paper, an ANN based approach for diagnosis of fault is suggested. Three phase current inputs are taken as inputs to train, test and validate fault data using MATLAB software [5].

6. "Transmission lines Fault Detection and Classification Using Deep Learning Neural Network," by authors J. Rajasekhar and A. Yadav, this paper used recent deep learning-based technique for fault detection and classification of different symmetrical and unsymmetrical transmission line faults. Main input parameter to the LSTM network is current signals which is measured at one end of IEEE 9- bus system using MATLAB/Simulink. Unlike the others techniques, LSTM does not require any separate feature extraction. This method can directly use for raw process data without feature extraction. The proposed result gives 100% accuracy for fault detection and 96.7% for fault classification [6].

7. "Electrical Faults-Detection and Classification using Machine Learning," authored by J. K, K. P, B. T V and J. A. Kovilpillai J. The paper focuses on machine learning (ML) techniques and algorithms for detection of transmission line faults. Different ML models such K-Nearest Neighbour, Support Vector Machine), LSTM (Long short-term memory), Decision Tree, Random Forest Classifier were developed to analysed the detection of various transmission line faults. The experimental results shows that SVM model detects better than the rest of models developed with a score of 0.9969 scores in confusion plot [7].

8. "Detection And Categorization of Transmission Line Faults Using Artificial Neural Network," authored by T. Gunasekar, P. Kokila, T. Mohanasundaram and D. Livinkumar. In this paper, transmission line faults are detected and categorize using ANN. The inputs to be fed to the ANN model is generated from a proposed transmission line system using MATLAB/Simulink. Generation of dataset is performed by giving different types of transmission line faults, varying fault location and changing the fault inception angle. It can be seen from the results that feed forward ANN model with back propagation can effectively detect, classify and locate 11 types of symmetrical and unsymmetrical faults [8].

9. "A LSTM Fault Diagnosis Method Based on Zero-sequence Voltage for Small Current Grounding System," authored by C. Deng, Z. Liu, H. Ying and L. Xu. In this paper, LSTM and k clustering method is employed a distribution network connected with PV and energy storage. Zero sequence voltage harmonics is used as main parameter to analyse whether a single line to ground fault has occurred or not using a fault recording device. The identification of fault with this method is found to be 96% accurate and the proposed model can also give the moment at which fault has occurred [9].

10. "On-line Transmission Line Fault Classification using Long Short-Term Memory," M. Li, Y. Yu, T. Ji and Q. Wu. The paper presents a novel hybrid approach of conventional LSTM with calibration training filter for classification of transmission line faults. As the transmission line parameters vary, a filter is used to choose samples having similar pattern with the signal under diagnosis thereby reducing the complexity of training. The results show FC-LSTM gives better classification than other models such as ANN, SVM and conventional LSTM with very short time delay [10].

CHAPTER 3: DETECTION, CLASSIFICATION & LOCATION OF FAULTS IN SHORT TRANSMISSION LINE

3.1 System Modelling

A two-bus of 11kv at the sendingtransmission line system is proposed. The block diagram is shown below in Fig 2. The two buses are 11kv bus and 0.4 kv bus. A step-down transformer is used to reduce the voltage which is connected in between the two buses. A fault block is connected in between the two bus to create all kinds of faults such as LG, LL, LLL, and LLLG faults. To measure the three-phase voltage and current VI measurement block is used. And these measurement blocks are connected to Artificial Neural Network Block in order to train the neural network for different types of faults.

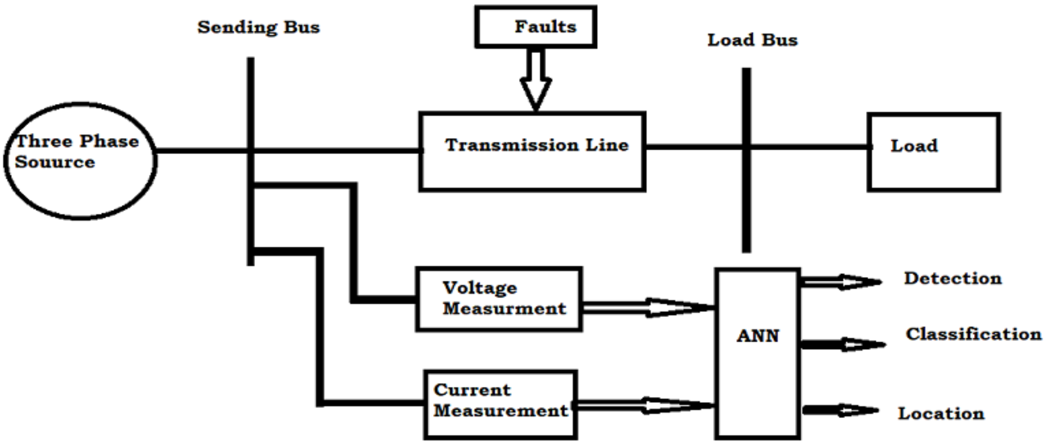

Fig 2 Block Diagram of Proposed Model

3.1.1 Transmission Line Pi Model

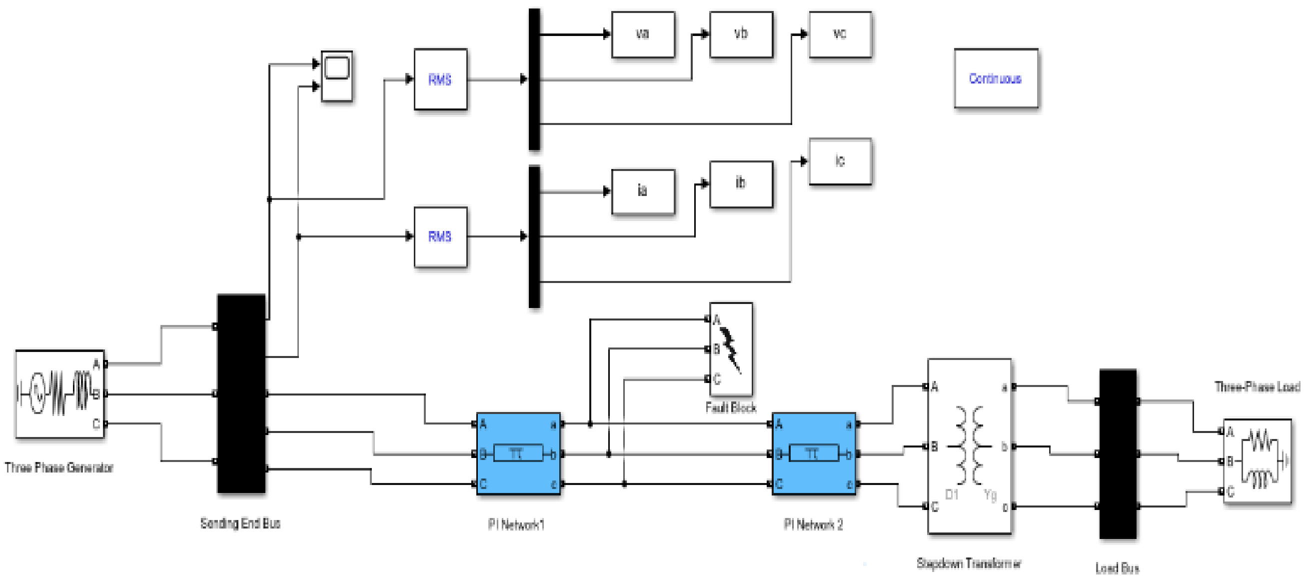

Fig 3 Transmission line Pi Model

A 11kv single end fed transmission line with a sending and load bus with a length of 25km is modelled in MATLAB/Simulink. The Simulink diagram is given in Fig. The model consists of a source feeder (11kv,30MVA,50 Hz), a sending end bus, where voltage and current are measured, a two Pi section lines for implementing the 25 km long transmission line, a fault block to create artificial fault, a Load bus, 11kv/0.4kv step down Transformer and a 20 MW Load. The specifications of the transmission Simulink model are given in table 1.

Table 1 Specifications of the Transmission Line Pi model.

Specifications	Values
Length	25 km
Load	10 KW Resistive, 20MVar Inductive
AC source Feeder	11kV, 30MVA, 50Hz
Three-Phase Transformer	11KV/0.4KV,1MVA, Delta-Star
Zero Sequence Resistance	0.3864 Ohm
Zero Sequence Inductance	4.1264 mH
Zero Sequence Capacitance	7.751 uF
Positive Sequence Inductance	0.9337mH
Positive Sequence Capacitance	12.74uF
Positive Sequence Resistance	0.01273Ohm

3.1.2 Dataset Generation

Fault dataset for training neural network is obtained by varying the fault location for various types of faults. The chosen parameters are given in Table 2

Table 2 Parameters Chosen

Parameters	Set Values
Fault Type (NO FAULT, LG, LL, LLG, LLL, LLLG)	NO FAULT, AG, BG, CG, AB, BC, CA, ABG, BCG, CAG, ABC, ABCG
Fault Location	5, 10, 15, 20, 25, 30, 35, 40, 45, 50(Km)

3.1.3 Different types of Faults and their Waveforms

1. NO Fault

The above figure shows the normal voltage and current waveforms that is No Fault Condition. It can be observed that all the three phase A, B, C (Yellow, Blue, Red) has the same voltage and current magnitude.

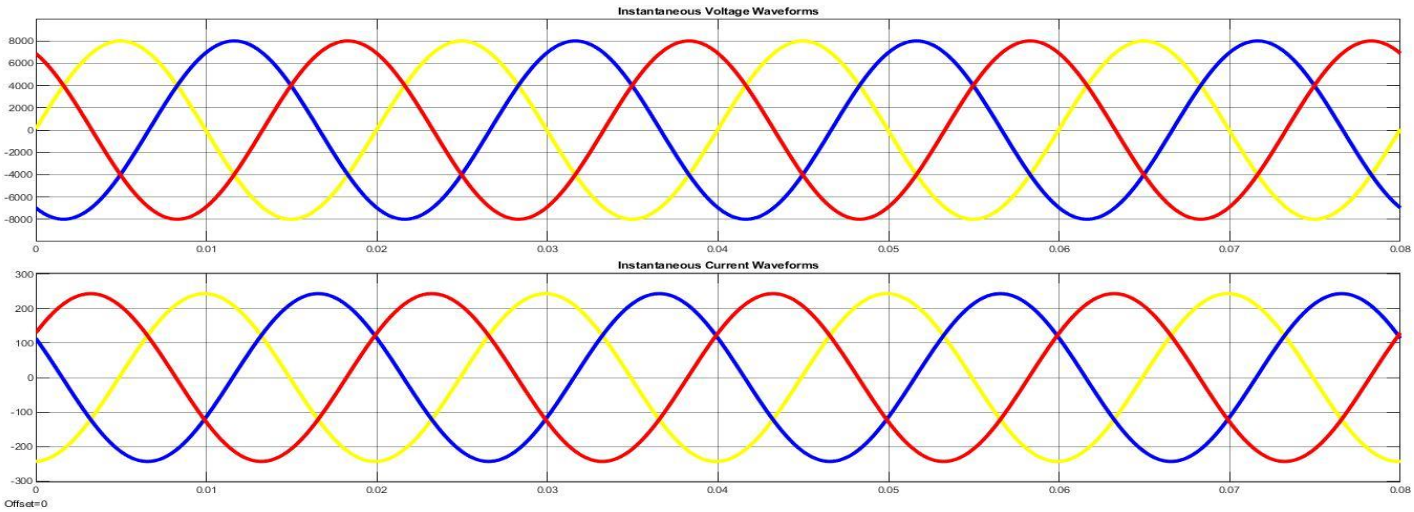

Fig 4 Voltage current waveforms of No fault

2. Single-Phase to Ground Fault

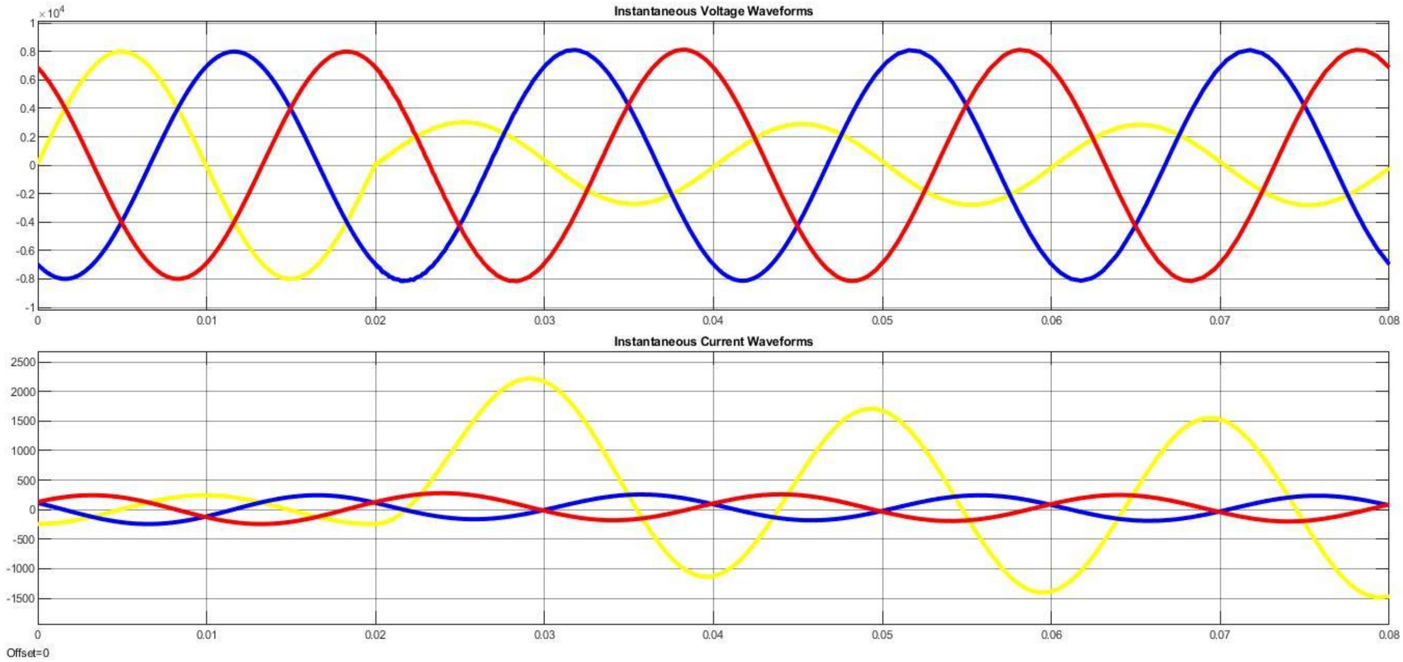

Fig 5 voltage current waveform for AG fault

A single phase to ground (AG) fault is applied at t=0. 02s.The fault was introduced at Length= 3km from the Sending Bus with fault resistance 0.1 Ohm and ground resistance 0.01 Ohm. In Fig b, Phase is A (Yellow) It can be observed that fault occurs at t=0.02s, and it can be seen the magnitude of Phase A current increases from normal and the magnitude of Phase A Voltage decreases

3. Two-phase (AB) fault

A phase-to-phase fault is applied at t=0.02s. The fault was introduced at Length=1km from Sending Bus with fault resistance 0.001 ohm. The above Fig shows Voltage and Current waveforms for AB fault. It can be seen that fault current is present only in phase A and B (Yellow and Blue) and fault voltage magnitude of phase A and B is same.

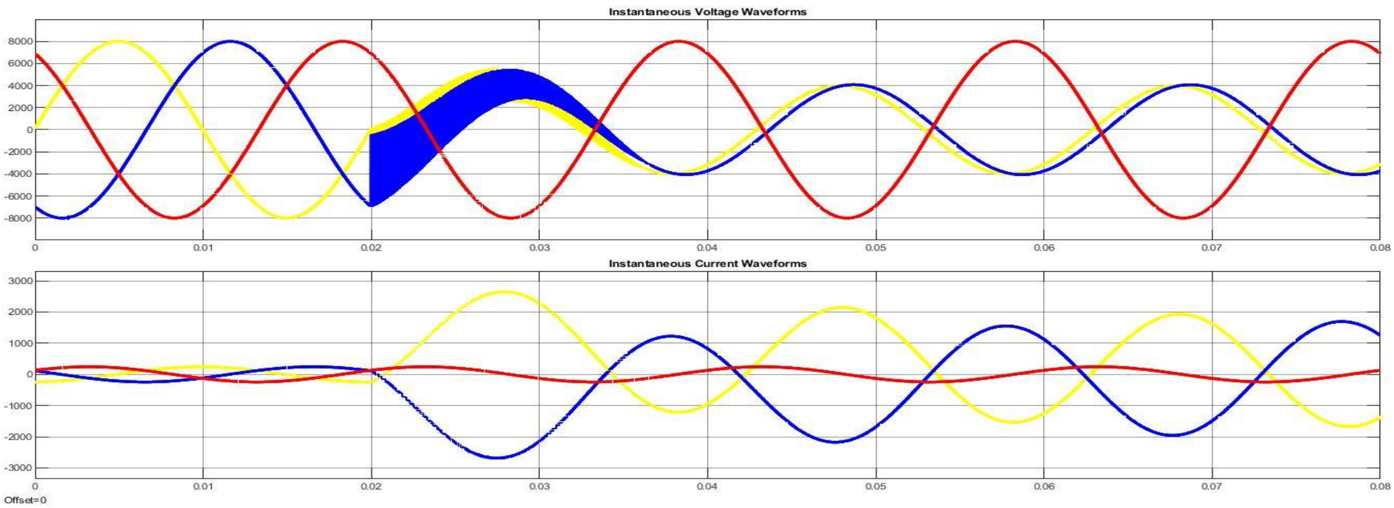

Fig 6 Voltage current waveform for AG fault

4. Two phase to Ground Fault (BCG)

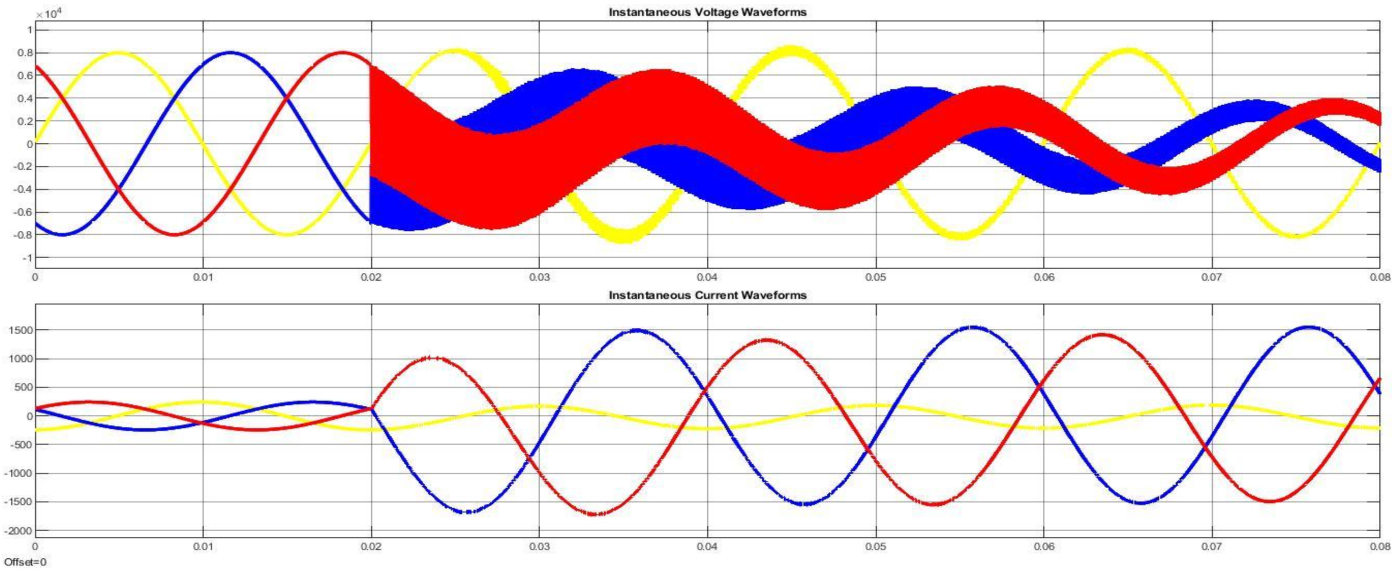

Fig 7 Voltage current waveform for BCG fault

A two-phase ground, BCG Fault is introduced at t=0.02s. The fault was introduced at L=5km from the sending end bus with fault resistance 0.001ohm. Fig shows the instantaneous voltage and current waveforms. It can be observed that phase B and C (Blue and Red) have fault. However due to the involvement of Ground, phase A(Yellow) also has distortions.

5. Three-Phase (ABC)fault

A three phase Fault ABC was applied at t=0.02s at Length =5km from the Sending Bus. The above figure shows the instantaneous Voltage and current waveforms. It is observed that all the three phases A, B, C are faulty.

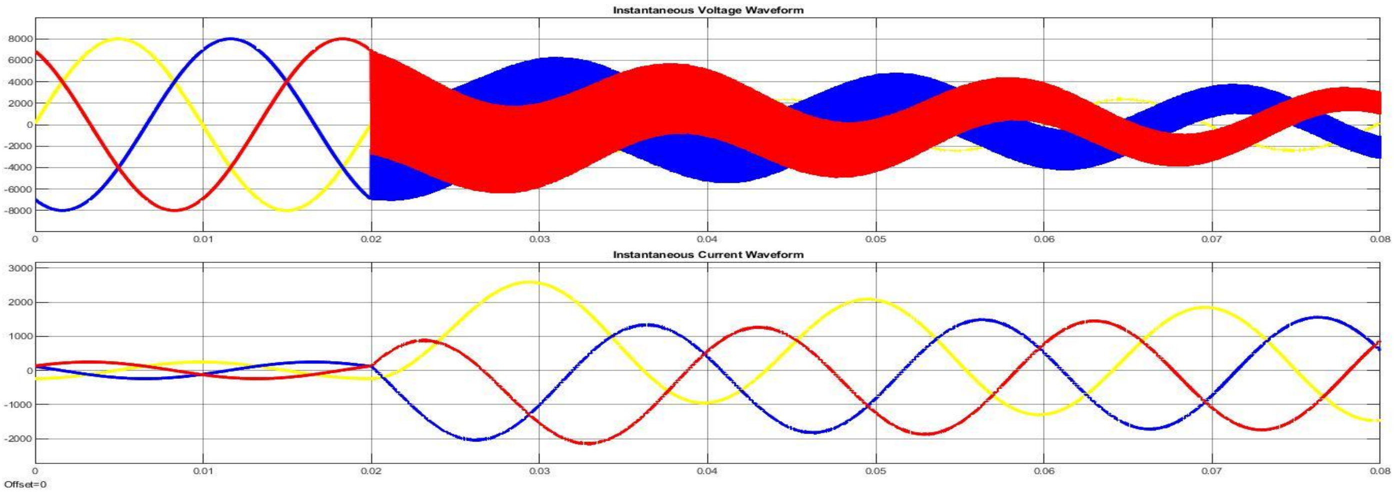

Fig 8 Voltage Current waveform for ABC fault.

6. Three Phase to Ground (ABCG) fault

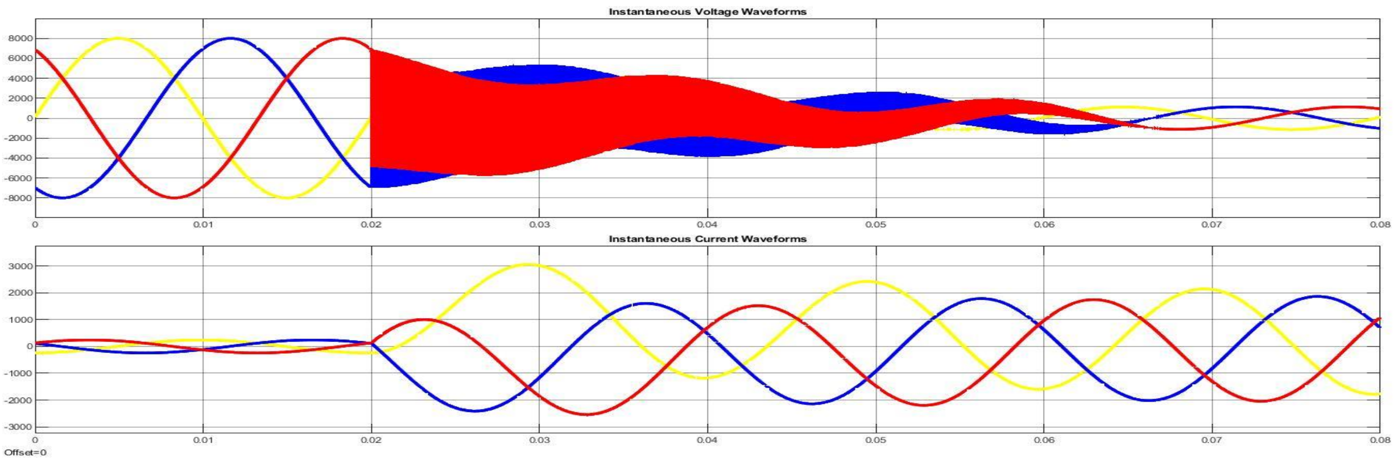

Fig 9 Voltage current waveform for ABCG fault

A three-phase ground (ABCG) fault is applied at t=0.02 s at Length=2km from the Sending Bus with fault resistance 0.001ohm. the fig shows the instantaneous Voltage and Current waveforms. It can be observed that all the three phases (A, B, C) are faulty. However due to the presence of Ground there is more distortion. And it can also be observed that when the fault length decreases from the Sending Bus, the more is the voltage drop.

3.2 Implementation of ANN

3.2.1 Basic architecture of ANN

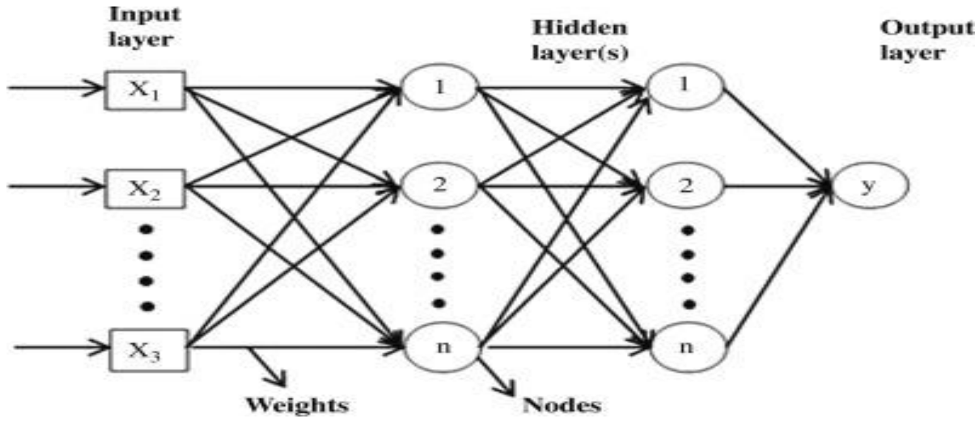

Fig 10 General Structure of ANN

ANN are data driven computing system that mimic the structure and functioning of biological neurons. It consists of neurons arranged in layers similar to neurons in brain. Feedforward neural network is the most commonly used neural network which consists of input layer to receive the input data, an output layer which gives the result, and a hidden layer as an intermediate layer which separates the other layers. It is the simplest neural network and data are process only in one direction, from input to output via hidden layer. The ease in designing and implementation of ANN, requirements of simple input features are some of the advantages of ANN. However, the disadvantages are requirement of large training dataset, no standard rule to design the network. There is no appropriate guidance in choosing the of neurons required, number of hidden layers and type of activation function. These are completely users' choice.

Training techniques can be supervised or unsupervised. In supervised training, both the input data and output data are known whereas in unsupervised learning only input data is provided to the network. In this study, feedforward neural network is trained with backpropagation algorithm. In backpropagation, starting with the final step and sending back the recalculated error, error at every iteration is adjusted. After every iteration the weights in backpropagation algorithm are updated and the process repeats for all input output set in the training dataset until minimum error is reached.

3.2.2 Design of ANN Fault Detector

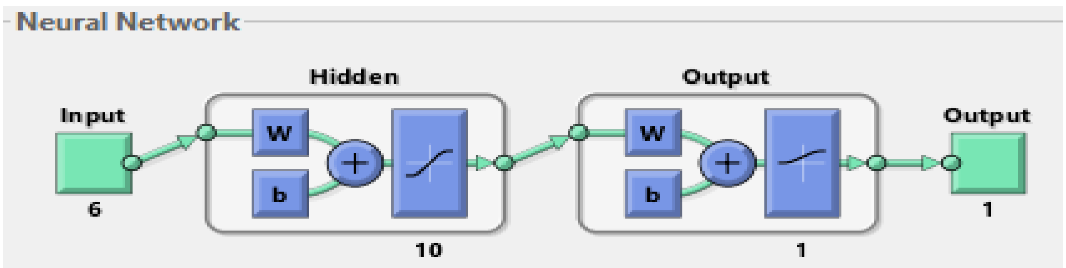

Fig 11 ANN detector Architecture

The ANN is designed with 6-10-1 configuration which means one input layer of 6 neurons, a hidden layer consisting of 10 neurons and 1 output layer of one neuron as shown in Fig 11 The input features to the neural network are the three phase RMS voltages (Va, Vb, Vc) and currents (Ia, Ib, Ic). Out of the total 1200 samples, 840 samples (70%) are used for training, and 180 samples (15%) each for testing and validation purpose. The target output for Fault detector is binary number i.e., 0 corresponds to non-faulty and 1 indicates faulty.

Scaled Conjugate Gradient Backpropagation algorithm is used to train the ANN detector neural network and performance is evaluated using MSE (Mean Square Error). The training convergence is shown in Fig 12. Best validation performance plot is 0.00010435. The validation line and test line in the convergence plot overlaps with the best line, this shows the convergence has occurred and the neural network model is effectively trained. The confusion plot in Fig 13 shows 100% detection of faults.

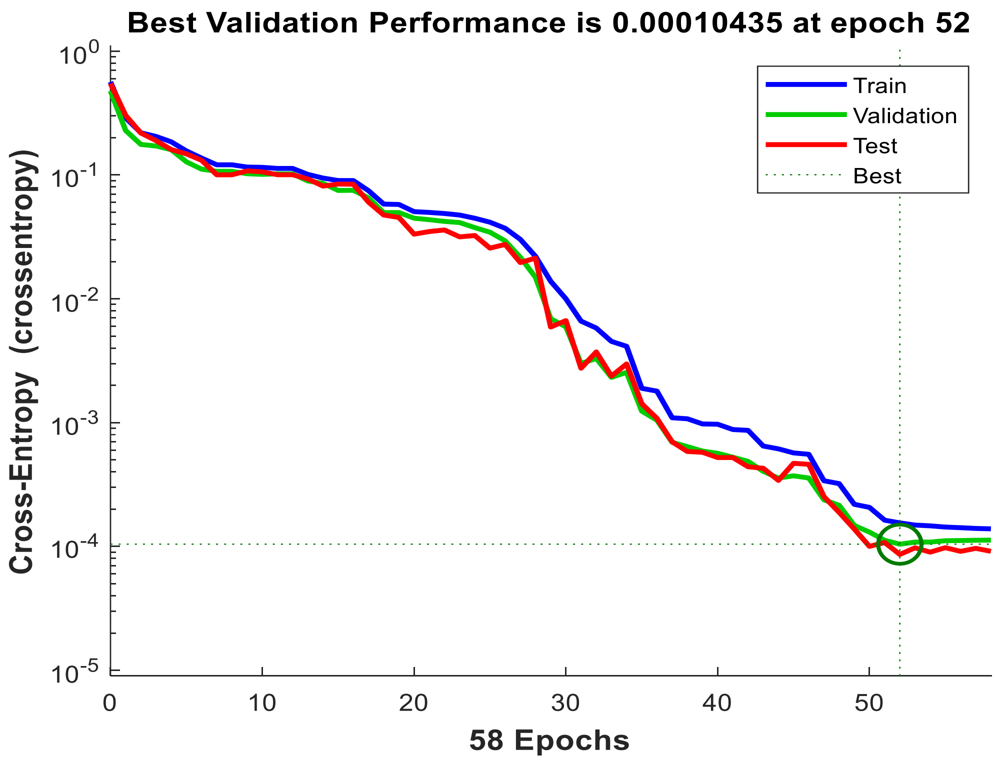

Fig. 12 MSE training Convergence for ANN Detector

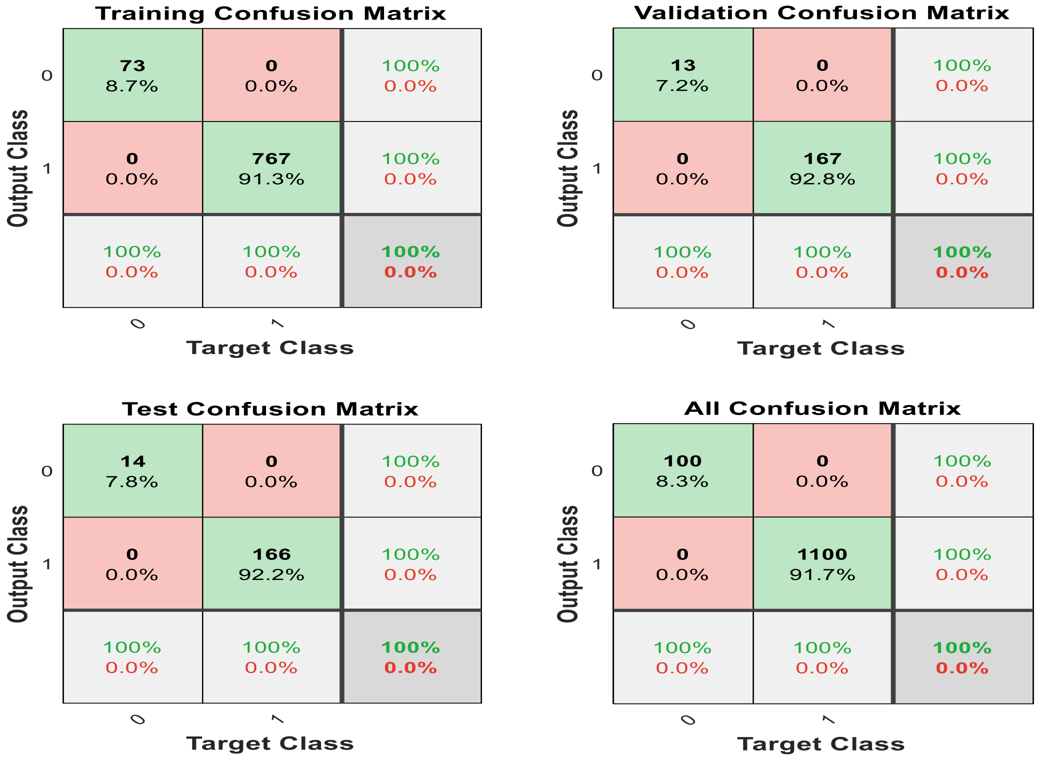

Fig 13 Confusion Plot for Fault Detection

Fig 14 shows the voltage-current waveform when A-B-C fault occurs. Fault is applied at 0.02s at 5km from the sending end bus with fault resistance 0.1Ω. All the three phases are faulty. It can be observed that during fault voltage amplitude drops whereas current amplitude increases. When fault is detected by the ANN Detector, the faulty signal raise from 0 to 1, which indicates the presence of fault.

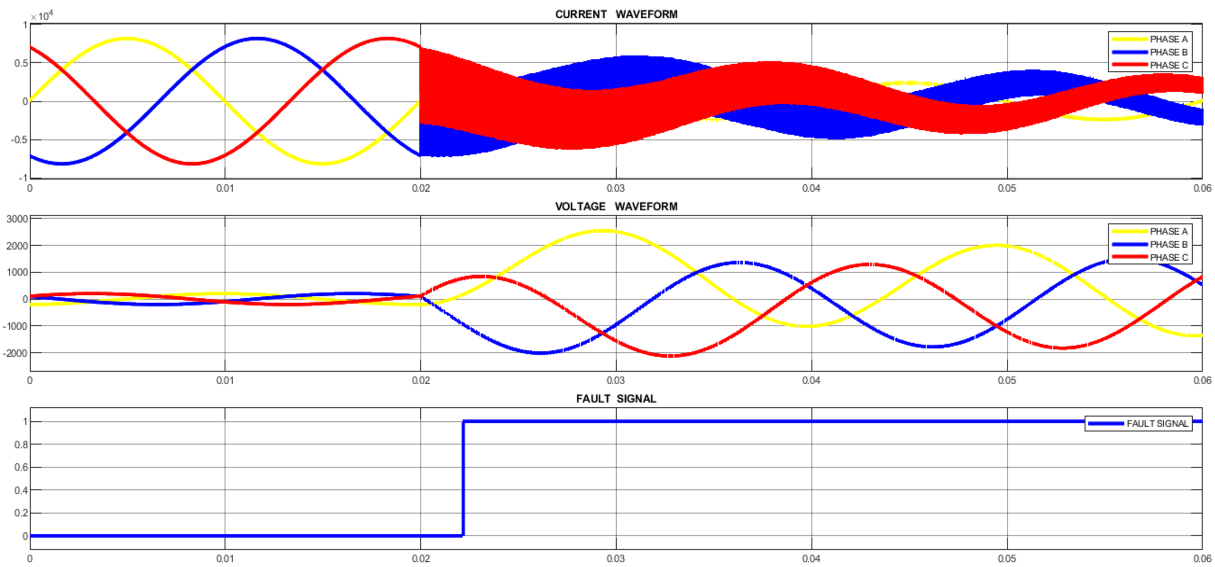

Fig 14 Waveforms for ABC Fault & Fault signal

Table 3 Truth Table for fault Detection

Sl. No	Type of Fault	ANN Output
1.	No Fault	0
2.	A-G	1
3.	B-G	1
4.	C-G	1
5.	A-B	1
6.	B-C	1
7.	A-C	1
8.	A-B-G	1
9.	B-C-G	1
10.	A-C-G	1
11.	A-B-C	1
12.	A-B-C-G	1

3.2.3 Design of ANN for Fault Classification

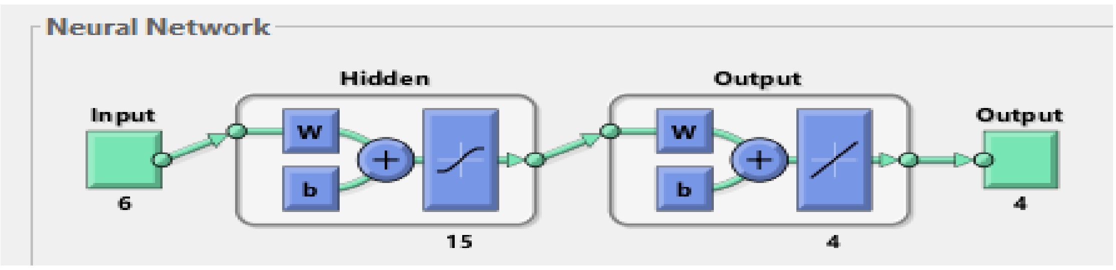

Fig 15 Architecture of ANN classifier

The classification network is having 6-15- 4 configuration, which means it has 6 inputs and 4 outputs. The four target output data showing the fault condition of the 3 phase lines A, B, C as well as the ground G in which 1 and 0 state representing whether the fault was happened or not. Three outputs indicate the status of three phases, if there is a fault in the system, then it is indicated by '1', else with '0'. Fourth output is used to indicate ground fault. If at all, in the fault, ground is present, then that is going to be shown by '1' else with '0'. The last output is used to indicate faults distance from the sending bus

The neural network has been trained with feed forward Back propagation network with different configuration of transfer function. Preferred network has an 6-neuron input layer, a 15-neuron hidden layer, and four neuron output layers as indicated in Fig 15. The Levenberg-Marquardt training algorithm has been used to train the neural network. The neural network is trained with a total 1200 cases.

The Levenberg-Marquardt (LM) algorithm, a variant of the back propagation algorithm, was utilized for neural network training as it is one of the quickest methods for training feed forward neural networks of moderate size.

Table 4 Truth Table for fault classification

Fault Type	**Phase A**	**Phase B**	**Phase C**	**Ground**
No Fault	0	0	0	0
A-G	1	0	0	1
B-G	0	1	0	1
C-G	0	0	1	1
A-B	1	1	0	0
B-C	0	1	1	0
A-C	1	0	1	0
A-B-G	1	1	0	1
B-C-G	0	1	1	1
A-C-G	1	0	1	1
A-B-C	1	1	1	0
A-B-C-G	1	1	1	1

Fig 16 shows the convergence plot where training, testing and validation lines overlaps with the best lines. This shows the convergence and training is effective. The best validation performance is 0.008692. The regression coefficient is obtained as 0.98338 which is approximately 98.3%.

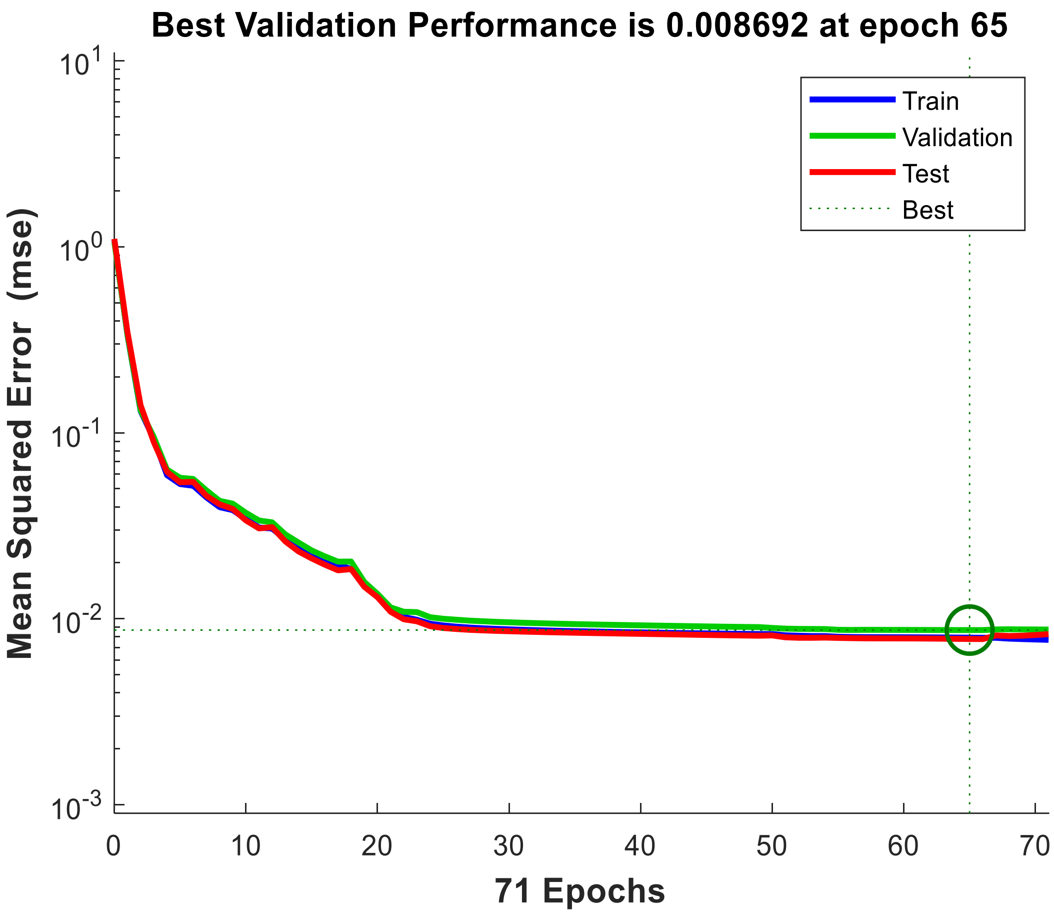

Fig 16 MSE training convergence plot of ANN Fault classifier

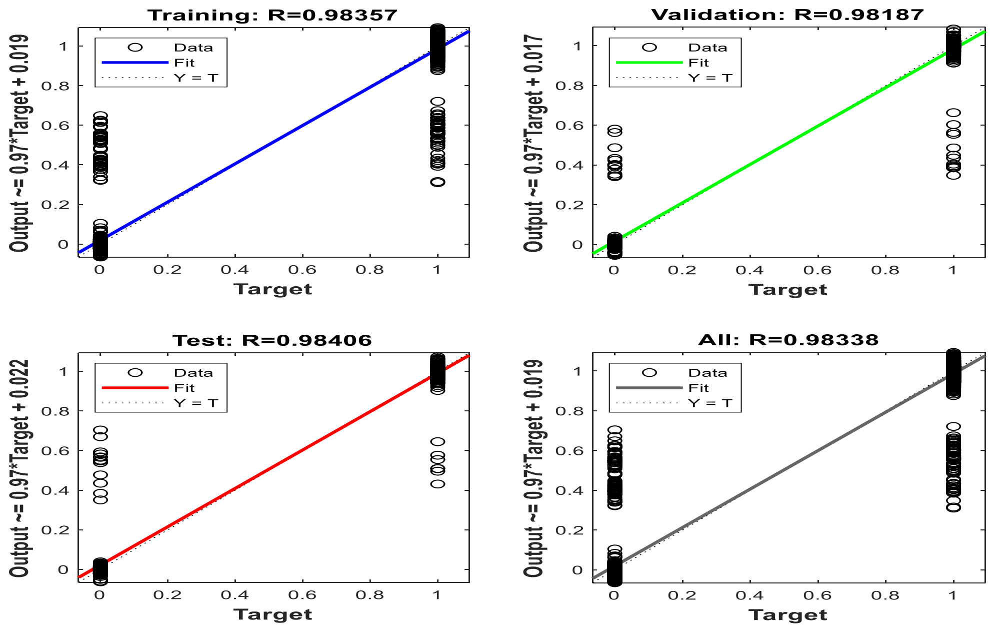

Fig 17 Regression plot for ANN classification

3.2.4 Design of ANN Fault Locator

Based on the transient characteristics, fault is detected then classified. Further step is to accurately identify the location to eliminate it, thereby saving cost and time. Similar to the above cases, ANN is trained with six inputs (Va, Vb, Vc, Ia, Ib, Ic). The network is trained using Levenberg-Marquardt (LM) algorithm. The ANN is designed with 6-20-1 configuration which means 6 inputs, 20 neurons in the hidden layer, and 1 output. 70% of the dataset is used for training, 15% for testing and 15% for validation.

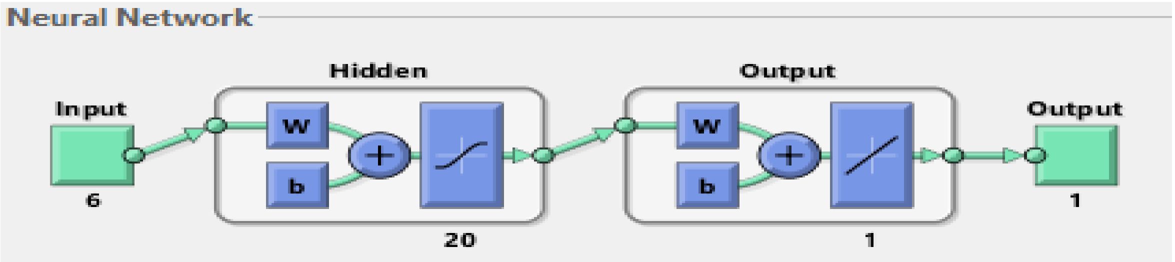

Fig 18 Architecture of ANN Locator

Fig 18 shows the architecture of ANN Locator. The ANN is designed with 6-20-1 configuration which means 6 inputs, 20 neurons in the hidden layer, and 1 output. 70% of the dataset is used for training, 15% for testing and 15% for validation.

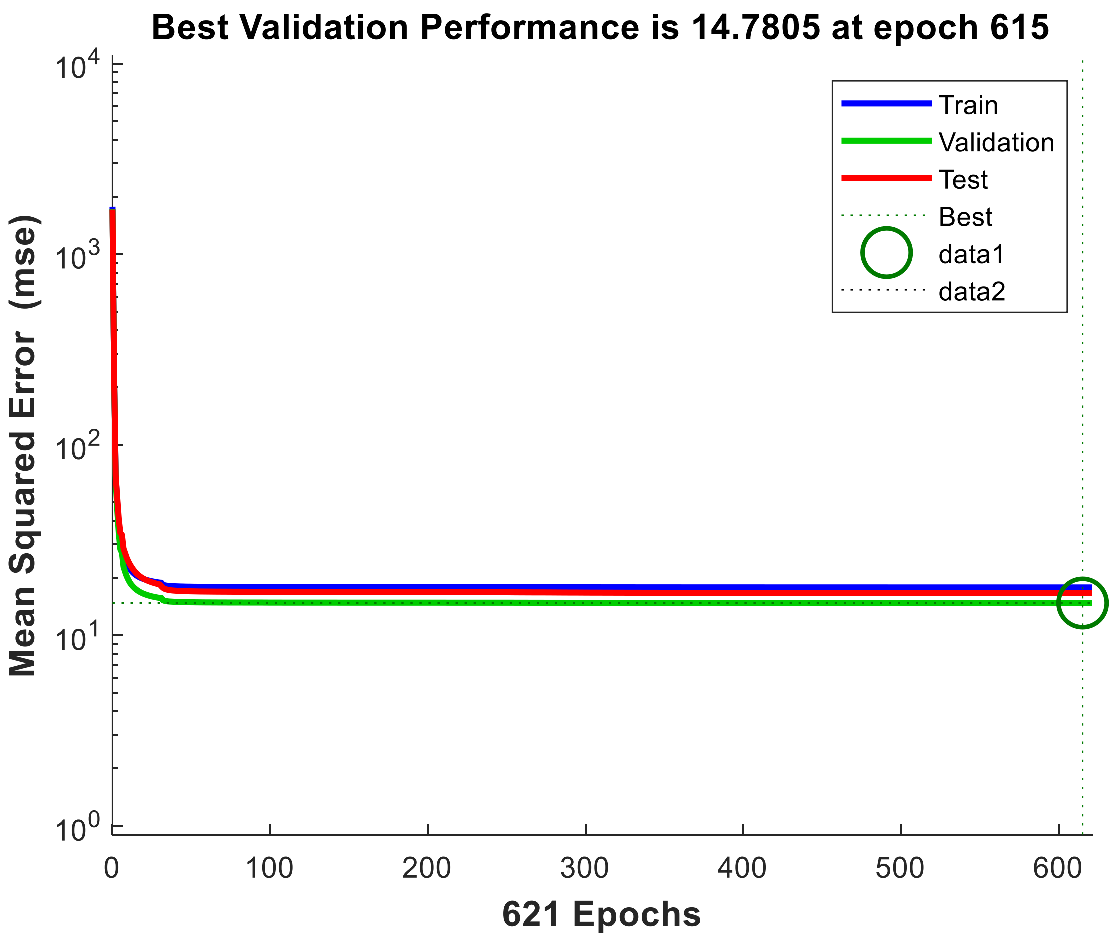

Figure 19 MSE training Convergence for ANN Locator

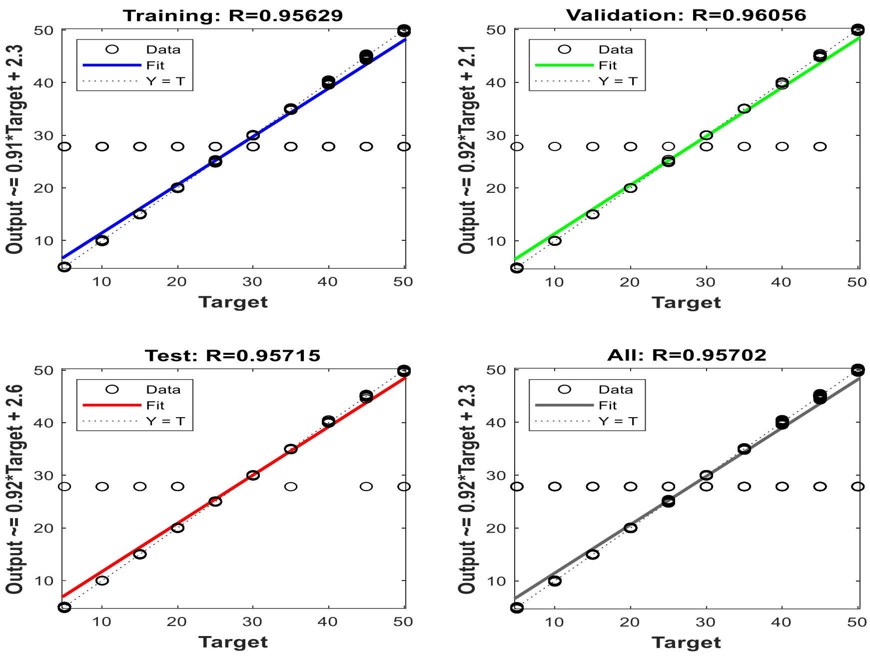

Fig20 Confusion Plot for Fault Location

Table 5 shows output of Fault Locator. The error between the predicted fault distance by the network and actual fault distance is small. The performance of Fault locator is satisfactory.

Table 5 ANN Output for Fault Locator

Fault type	**Actual Fault distance (in Km)**	**Distance predicted by ANN Fault locator**	**Error**
A-G	18	18.04	0.04
B-G	45	45.77	0.77
C-G	43	43.08	0.08
A-B	31	31.32	0.32
B-C	22	22.09	0.09
A-C	13	13.4	0.40
A-B-G	9	9.03	0.03
B-C-G	11	11.19	0.19
A-C-G	36	36.4	0.40
A-B-C	50	50.22	0.22
A-B-C-G	9	8.39	0.61

3.3 Conclusion

Major quality problems in transmission and distribution network are the electrical faults and its impact on the end user’s load. In fact, it is the largest contributor to power system instability. Therefore, to maintain the stability of the electric grid system is the top priority of power industry.

In this study, ANN is implemented as a technique to detect, classify and locate faults on a 11kV/0.4kV, 55 km short transmission line. The three-phase voltage and current signals generated by simulating the proposed model are taken as inputs to train the feed forward ANN neural network and back propagation algorithm is adopted for training purpose.

From the proposed model, the detection of faults is achieved with very high accuracy. The classification regression coefficient is obtained as 0.9833 which is near to 1, this indicates close relationship between targets and outputs. In the fault location, the error obtained by the ANN locator are satisfactory.

CHAPTER 4: DETECTION, CLASSIFICATION OF FAULTS IN MEDIUM TRANSMISSION LINE

4.1 Medium Transmission Line Fault Dataset Collection

A two-bus of and medium transmission line model is developed using MATLAB/Simulink. It consists of a three-phase source of 132KV and 33KV is used. A step-down transformer is used to reduce the voltage which is connected in between the two buses. A fault block is connected in between the two bus to create all kinds of faults such as LG, LL, LLL, and LLLG faults. To measure the three-phase voltage and current VI measurement block is used. The measured Three phase RMS voltage and current is used as input to different neural network. A total of 4400 fault dataset samples were generated for both detection and classification purpose. Fig 21 shows the Simulink diagram developed to generate the dataset. The detail specifications of Simulink model is given in table 6.

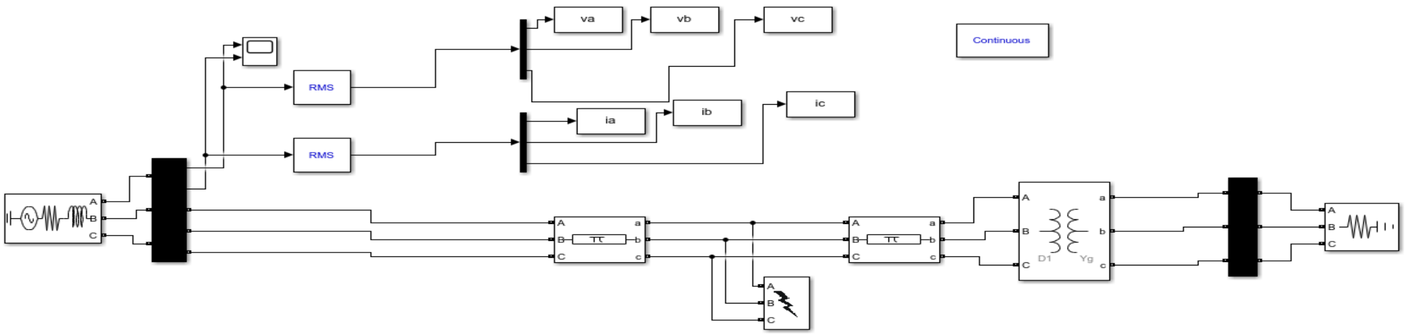

Fig 21 Simulink model of medium transmission line

Table 6 Specifications of Medium Transmission line pi model

Specifications	Values
Length	105 km
Load	20MW Resistive
AC source Feeder	132kV, 30MVA, 50Hz
Three-Phase Transformer	132KV/33KV,30MVA, Delta-Star
Zero Sequence Resistance	0.3864 Ohm
Zero Sequence Inductance	4.1264 mH
Zero Sequence Capacitance	7.751 uF
Positive Sequence Inductance	0.9337mH
Positive Sequence Capacitance	12.74uF
Positive Sequence Resistance	0.01273Ohm

Table 7 Parameter variation for fault dataset generation

Parameters	Set Values
Fault Type	NO FAULT, AG, BG, CG, AB, BC, CA, ABG, BCG, CAG, ABC, ABCG
Fault Location	5, 10 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100(km)

Table 8 Characteristic of Generated Signal

Signal	3 phase RMS Voltage and Current Signal
Sampling	4400
Data Size	6x 4400 samples
Number of Signals	6

The generated fault datasets are labelled as 0 and 1 for detection. It is shown in table. For Classification the different types of faults are assigned with numbers ranging from 1 to 12. These labels represent the output of detection and classification for all the models developed namely ANN model, CNN model and LSTM model considered in this study. Table 9 shows the fault type and assign label.

Table 9 Fault Type and assign label for fault detection

Type of Fault	Label
No Fault	0
A-G	1
B-G	1
C-G	1
A-B	1
B-C	1
A-C	1
A-B-G	1
B-C-G	1
A-C-G	1
A-B-C	1
A-B-C-G	1

Table 10 Fault Type and assign label for fault Classification

Type of Fault	Label
No Fault	1
A-G	2
B-G	3
C-G	4
A-B	5
B-C	6
A-C	7
A-B-G	8
B-C-G	9
A-C-G	10
A-B-C	11
A-B-C-G	12

4.2 Methodology

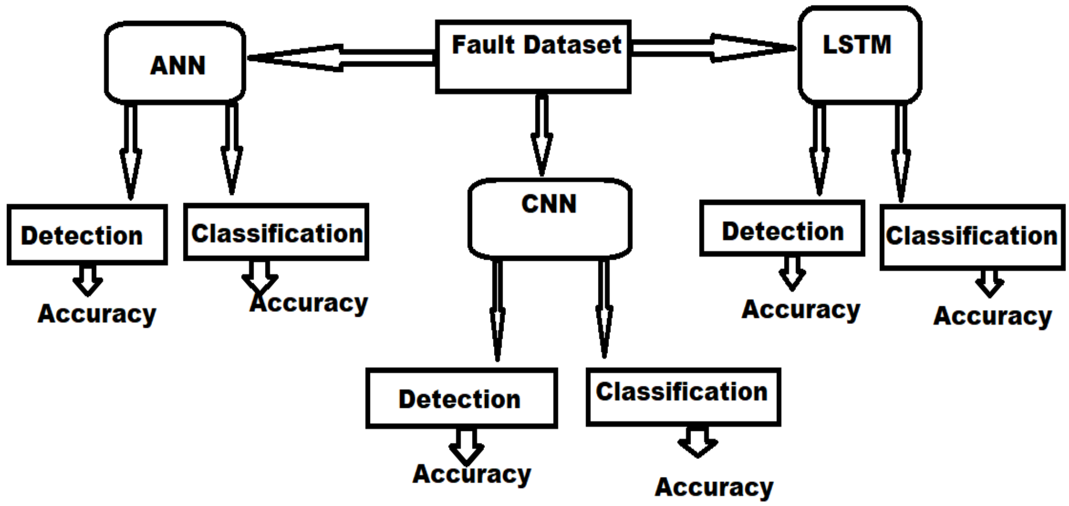

Fig 22 Workflow of Proposed Work

In this study, three algorithms namely ANN (Artificial Neural Network), CNN (Convolution Neural Network), LSTM (Long Short-Term Memory) will be implemented. Further basis structure and designing of models will be discussed elaborately in the following pages.

4.3 Shallow Neural Network Vs Deep Neural Network

Table 11 Shallow vs deep neural network

SL. No	Shallow Neural Network	Deep Neural Network
1.	It has only one hidden layer between input and output layers.	It has multiple hidden layers between input and output layers.
2.	It is used for simple tasks example. Image Classification.	It is used for complex tasks such as image segmentation, language processing, video classification
3.	Computationally less expensive	Computationally high expensive
4.	Less Accurate	Higher accuracy
5.	Simple to design	Complex to design
6.	Can handle simple data	Can handle complex data and patterns
7.	ANN	CNN, LSTM

4.4 Designing ANN model for Detection and Classification

4.4.1 Architecture of ANN for Detection and Classification

An input layer of 6 neurons, hidden layer of 10 neurons and one output layer of 1 neuron is configured for detection and classification of transmission line faults. The three phase RMS voltage and current is used as input to train the models. Out the total 4800 samples generated 70% is used for training. 15% for testing and 15% for validation. Performance of this model is checked for different training algorithm and their accuracy are compared.

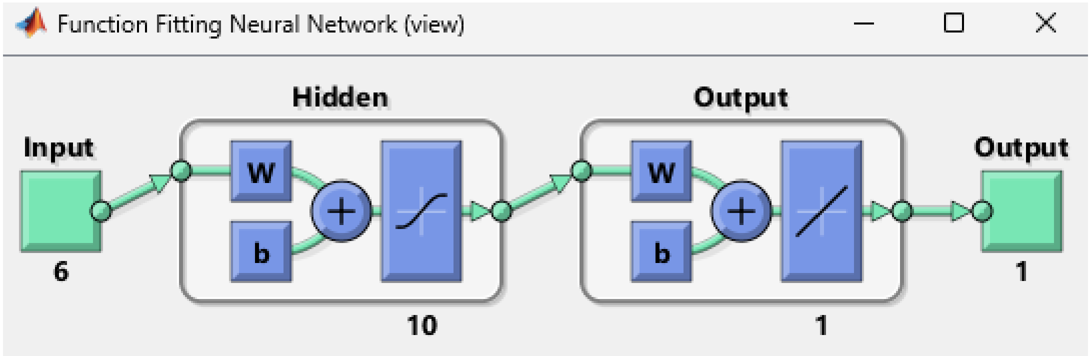

Fig 23 Architecture of ANN model for detection and classification

4.4.2 Performance Analysis for ANN Models

Table 12 Performance Record of ANN model

Hyper Parameters	Detection		Classification	
Epoch	50		50	
No of Signals	6		6	
No of Classes	2		12	
No of Layers	3		3	
Training Options	Trainlm	Trainscg	Trainlm	Trainscg
Accuracy in %	98.91	98.88	99.82	99.74
Computation Time	4.321098	11.584975	10.541782	25.176437

Regression plot for Detection using trainlm and trainscg are shown in Fig 24 and Fig 25.

Regression plot for Classification using trainlm and trainscg are shown in Fig26 and Fig 27.

Regression value near to 1 shows closer relationship between targets and output.

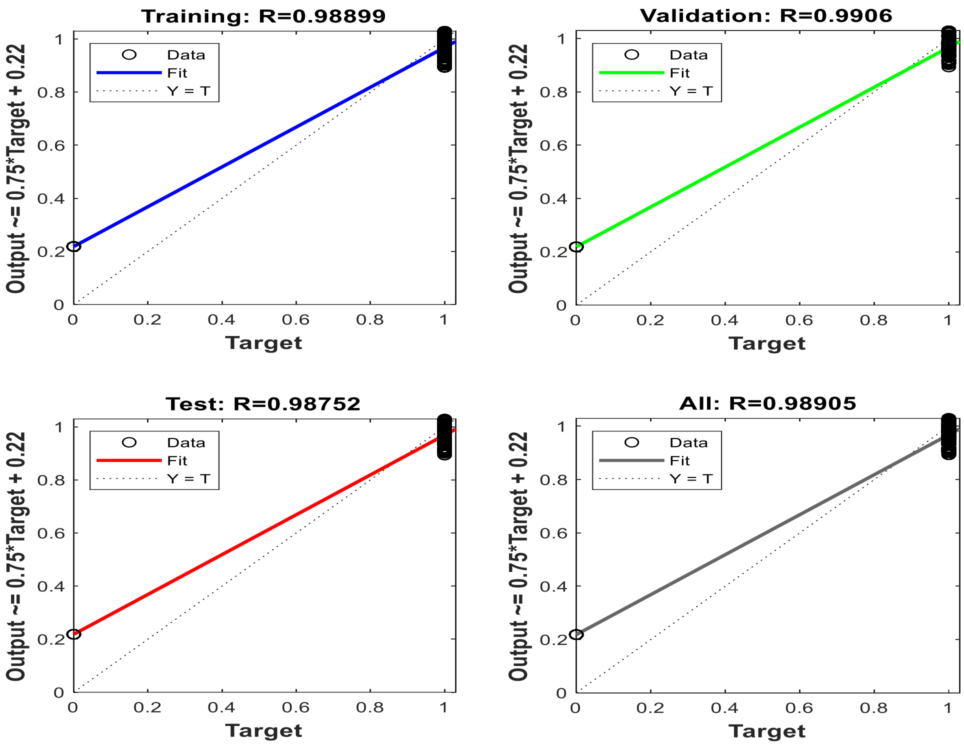

Fig 24 Regression Plot for Detection using trainlm

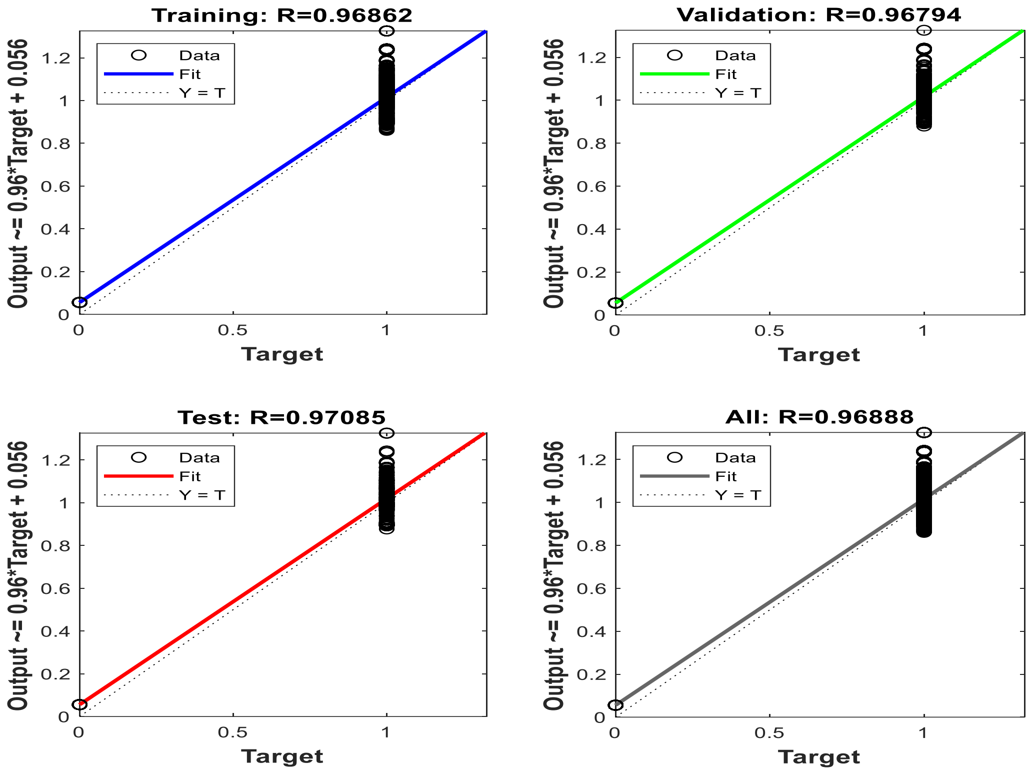

Fig 25 Regression Plot for Detection using trainscg

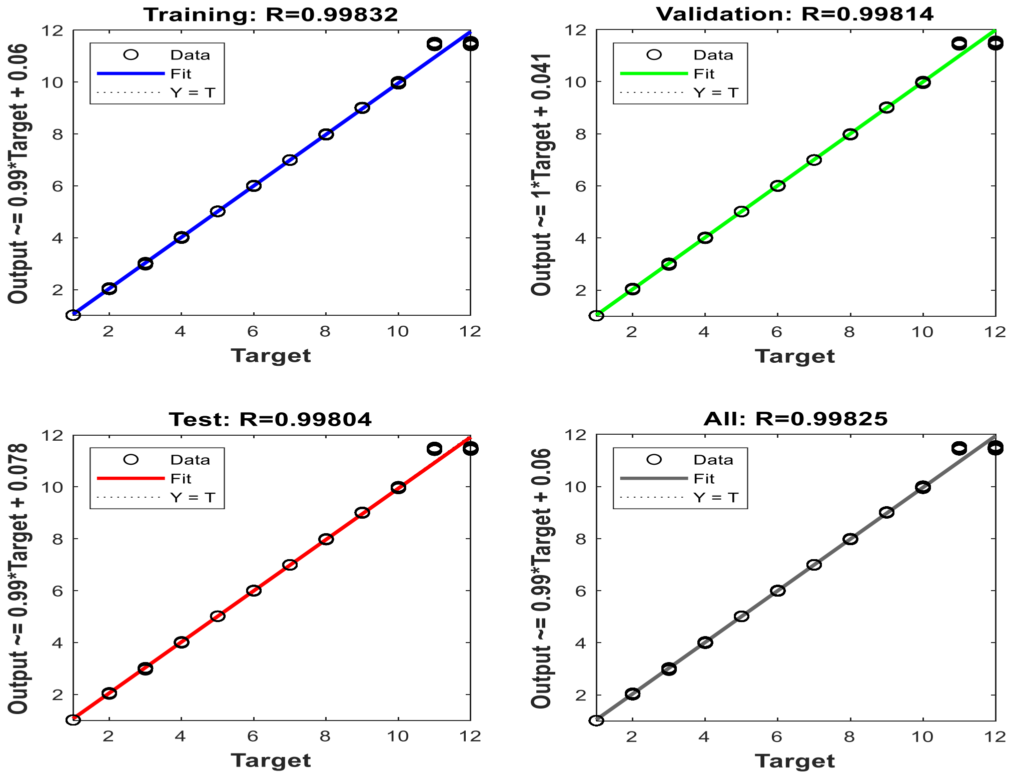

Fig 26 Regression plot for Classification using trainlm

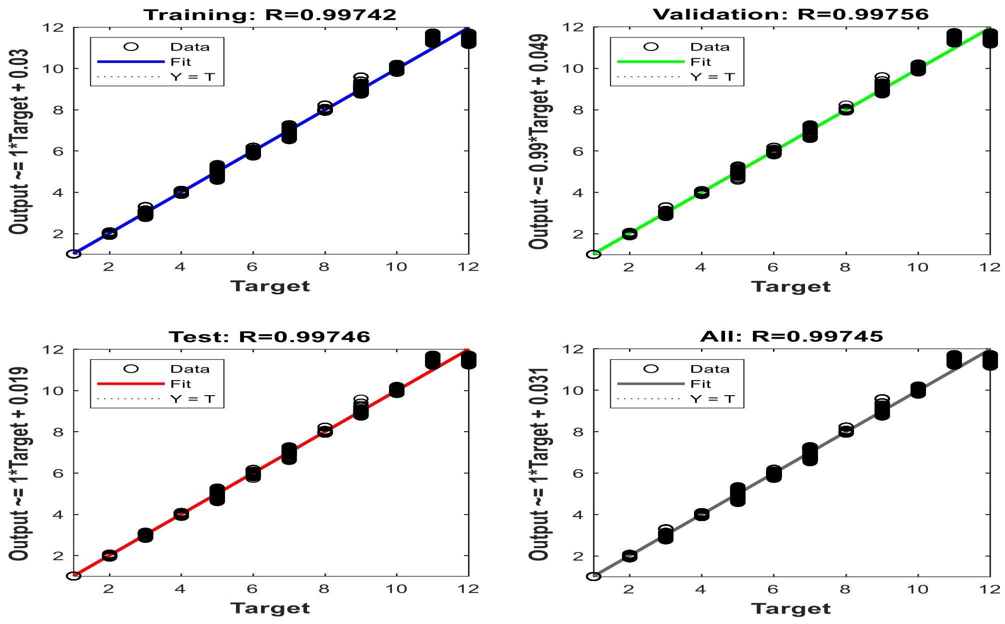

Fig 27 Regression plot for Classification using trainscg

4.4.3 Result Analysis

From the regression plot figures above, it is observed that ANN model with 'trainlm' training options perform better than ANN trained with 'sgdm' with an accuracy of 98.91% for detection and an accuracy of 99.74 % for classification. It can also conclude that 'trainlm' takes less computational time compared to 'trainscg'

4.5 CNN (Convolution Neural Network)

CNNs are a class of Deep Neural Networks that can recognize and classify particular features from images and are widely used for analysing visual images. Their applications range from image and video recognition, image classification, medical image analysis, computer vision and natural language processing. CNN has high accuracy, and because of the same, it is useful in image recognition. Image recognition has a wide range of uses in various industries such as medical image analysis, phone, security, recommendation systems, etc. The term 'Convolution" in CNN denotes the mathematical function of convolution which is a special kind of linear operation wherein two functions are multiplied to produce a third function which expresses how the shape of one function is modified by the other. In simple terms, two images which can be represented as matrices are multiplied to give an output that is used to extract features from the image. CNNs provide an optimal architecture for uncovering and learning key features in image and time-series data. CNNs are a key technology in applications such as:

1. Medical Imaging**:** CNNs can examine thousands of pathology reports to visually detect the presence or absence of cancer cells in images.

2. Audio Processing**:** Keyword detection can be used in any device with a microphone to detect when a certain word or phrase is spoken ("Hey Siri!"). CNNs can accurately learn and detect the keyword while ignoring all other phrases regardless of the environment.

3. Object Detection**:** Automated driving relies on CNNs to accurately detect the presence of a sign or other object and make decisions based on the output.

4. Synthetic Data Generation: Using Generative Adversarial Networks (GANs), new images can be produced for use in deep learning applications including face recognition and automated driving.

4.5.1 General Structure of CNN

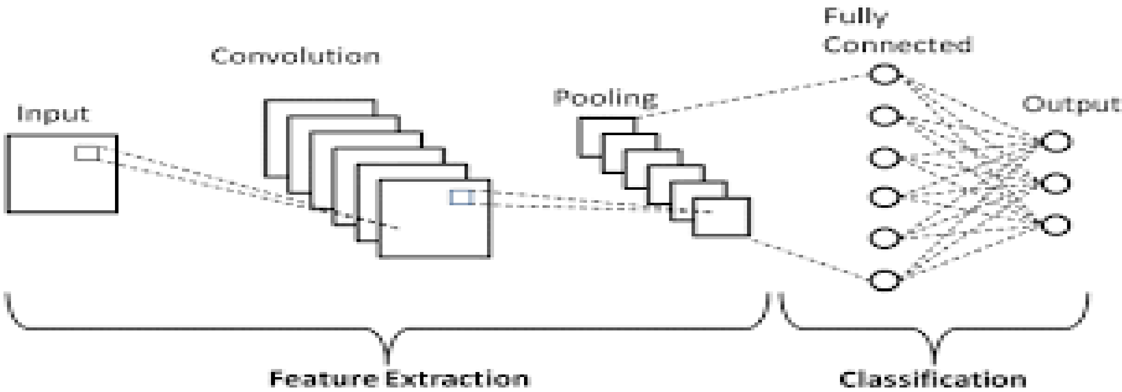

Fig 28 General Architecture of CNN

A CNN is composed of an input layer, an output layer, and many hidden layers in between. There are two main parts to a CNN architecture i.e., Feature Extraction and Classification. A convolution tool that separates and identifies the various features of the image for analysis in a process called as Feature Extraction. The network of feature extraction consists of many pairs of convolutional or pooling layers. A fully connected layer that utilizes the output from the convolution process and predicts the class of the image based on the features extracted in previous stages. This CNN model of feature extraction aims to reduce the number of features present in a dataset. It creates new features which summarises the existing features contained in an original set of features.

There are three types of layers that make up the CNN which are the convolutional layers, pooling layers, and fully-connected (FC) layers. When these layers are stacked, a CNN architecture will be formed. In addition to these three layers, there are two more important parameters which are the dropout layer and the activation function which are defined below.

a. Convolutional Layer- This layer is the first layer that is used to extract the various features from the input images. In this layer, the mathematical operation of convolution is performed between the input image and a filter of a particular size MxM. By sliding the filter over the input image, the dot product is taken between the filter and the parts of the input image with respect to the size of the filter (MxM). The output is termed as the Feature map which gives us information about the image such as the corners and edges. Later, this feature map is fed to other layers to learn several other features of the input image. The convolution layer in CNN passes the result to the next layer once applying the convolution operation in the input. Convolutional layers in CNN benefit a lot as they ensure the spatial relationship between the pixels is intact.

b. Pooling Layer -In most cases, a Convolutional Layer is followed by a Pooling Layer. The primary aim of this layer is to decrease the size of the convolved feature map to reduce the computational costs. This is performed by decreasing the connections between layers and independently operates on each feature map. Depending upon method used, there are several types of Pooling operations. It basically summarises the features generated by a convolution layer. In Max Pooling, the largest element is taken from feature map. Average Pooling calculates the average of the elements in a predefined sized Image section. The total sum of the elements in the predefined section is computed in Sum Pooling. The Pooling Layer usually serves as a bridge between the Convolutional Layer and the FC Layer. This CNN model generalises the features extracted by the convolution layer, and helps the networks to recognise the features independently. With the help of this, the computations are also reduced in a network.

c. Fully Connected Layer- The Fully Connected (FC) layer consists of the weights and biases along with the neurons and is used to connect the neurons between two different layers. These layers are usually placed before the output layer and form the last few layers of a CNN Architecture. In this, the input image from the previous layers is flattened and fed to the FC layer. The flattened vector then undergoes few more FC layers where the mathematical functions operations usually take place. In this stage, the classification process begins to take place. The reason two layers are connected is that two fully connected layers will perform better than a single connected layer. These layers in CNN reduce the human supervision.

d. Dropout-Usually, when all the features are connected to the FC layer, it can cause overfitting in the training dataset. Overfitting occurs when a particular model works so well on the training data causing a negative impact in the model's performance when used on a new data. To overcome this problem, a dropout layer is utilised wherein a few neurons are dropped from the neural network during training process resulting in reduced size of the model. On passing a dropout of 0.3, 30% of the nodes are dropped out randomly from the neural network. Dropout results in improving the performance of a machine learning model as it prevents overfitting by making the network simpler. It drops neurons from the neural networks during training. Activation Functions-Finally, one of the most important parameters of the CNN model is the activation function. They are used to learn and approximate any kind of continuous and complex relationship between variables of the network. In simple words, it decides which information of the model should fire in the forward direction and which ones should not at the end of the network. It adds non-linearity to the network. There are several commonly used activation functions such as the ReLU, SoftMax, tanH and the Sigmoid functions. Each of these functions have a specific usage. For a binary classification CNN model, sigmoid and SoftMax functions are preferred a for a multi-class classification, generally SoftMax us used. In simple terms, activation functions in a CNN model determine whether a neuron should be activated or not. It decides whether the input to the work is important or not to predict using mathematical operations.

How CNN works?

A convolutional neural network can have tens or hundreds of layers that each learn to detect different features of an image. Filters are applied to each training image at different resolutions, and the output of each convolved image is used as the input to the next layer. The filters can start as very simple features, such as brightness and edges, and increase in complexity to features that uniquely define the object.

4.5.2 Design of CNN model

The developed CNN model has 8 layers- a convolution layer, batch normalization layer, Relu Layer, Max Pooling Layer, drop out Layer, Fully Connected Layer, a dense layer having activation function of ‘SoftMax’ and a classification layer. The model is trained at 50 epoch both for detection and classification of faults. It is tested after the completion of training. And result is analysed based on the computational time and type of optimizer used during training. The fig below shows block diagram of CNN layers of the proposed model.

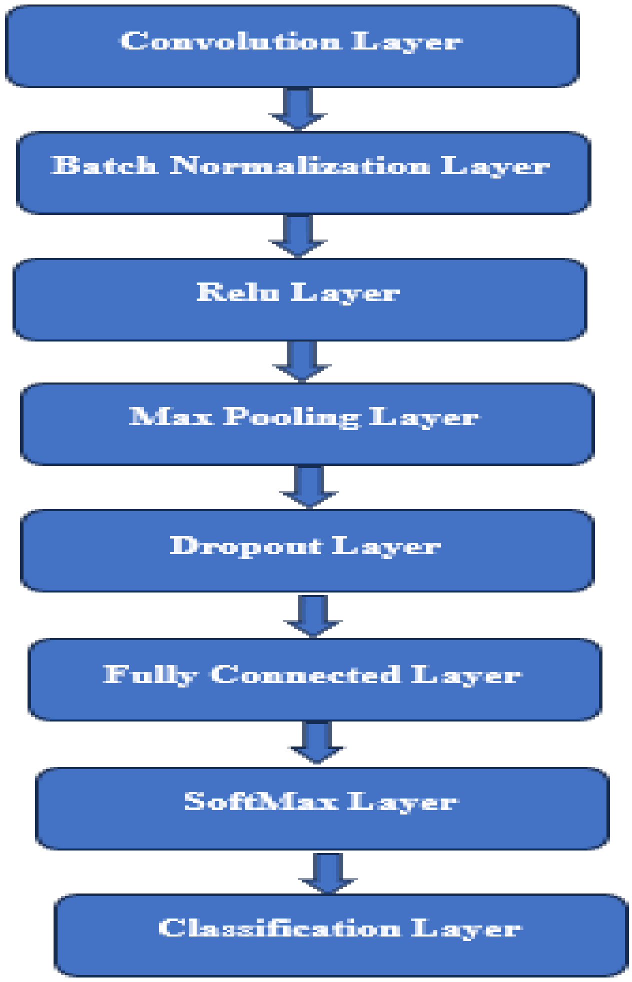

Fig 29 Block Diagram of Layers of Proposed CNN Model

4.5.3 Performance analysis of CNN model

Table 13 Hyperparameters for detection &classification CNN models

Hyper Parameters	**Detection**		**Classification**	
Epoch	50		50	
No of Signals	6		6	
No of Classes	2		12	
No of Layers	8		8	
Training Options	Adam Optimizer	Sgdm Optimizer	Adam Optimizer	Sgdm Optimizer
Accuracy in %	91.67	91.67	89.3	89
Computation Time	18.983302	19.790485	21.337300	21.719094

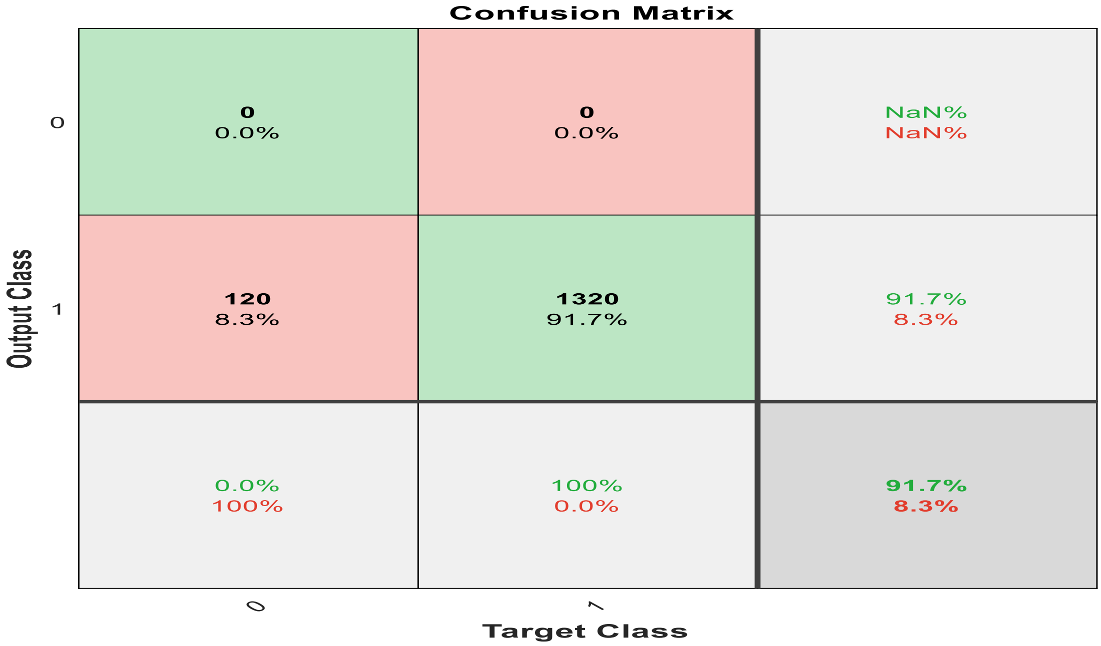

Fig 30 Confusion Plot for Detection using Adam Optimizer

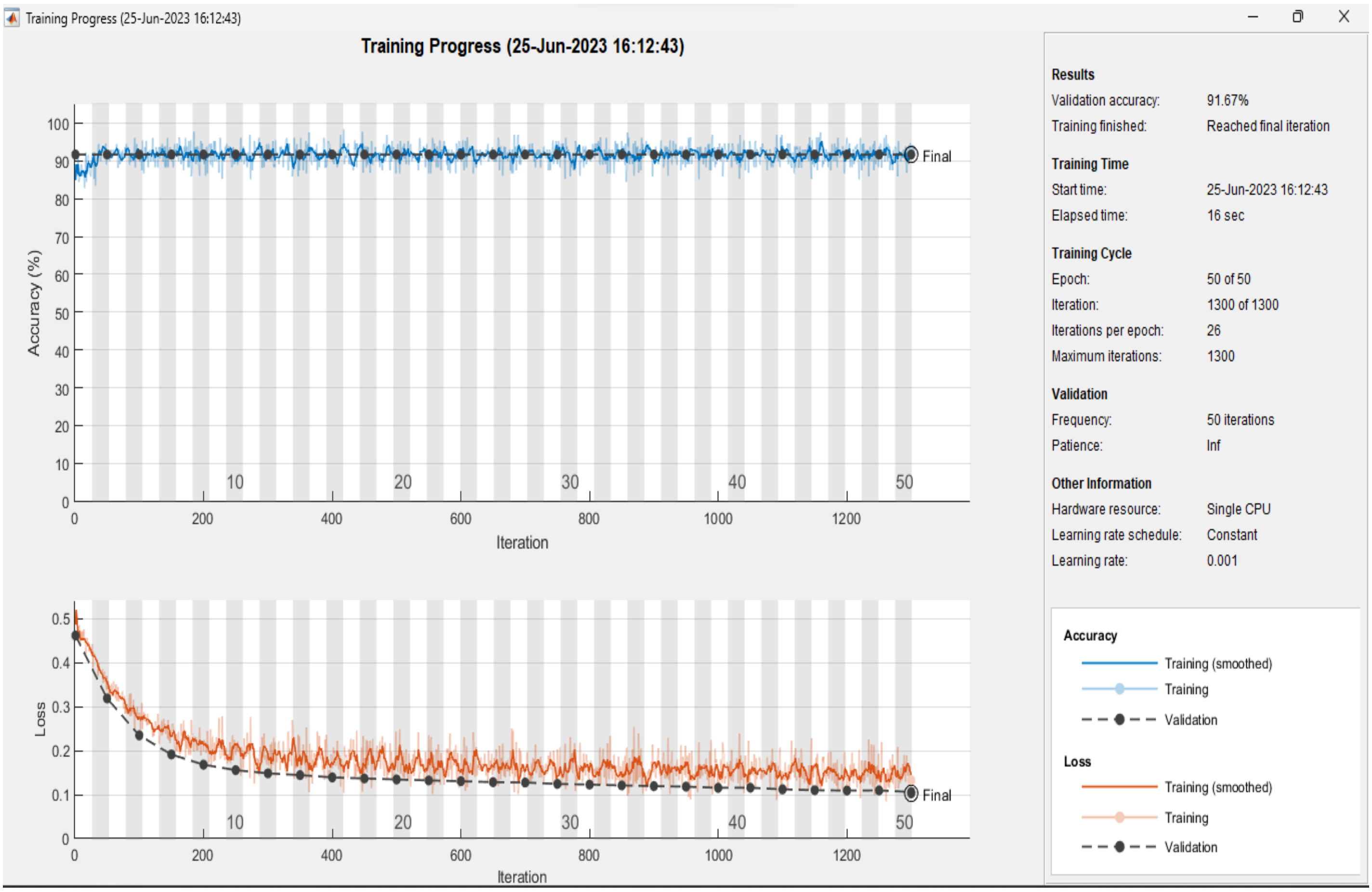

Fig 31 Training Progress plot for Detection using Adam Optimizer

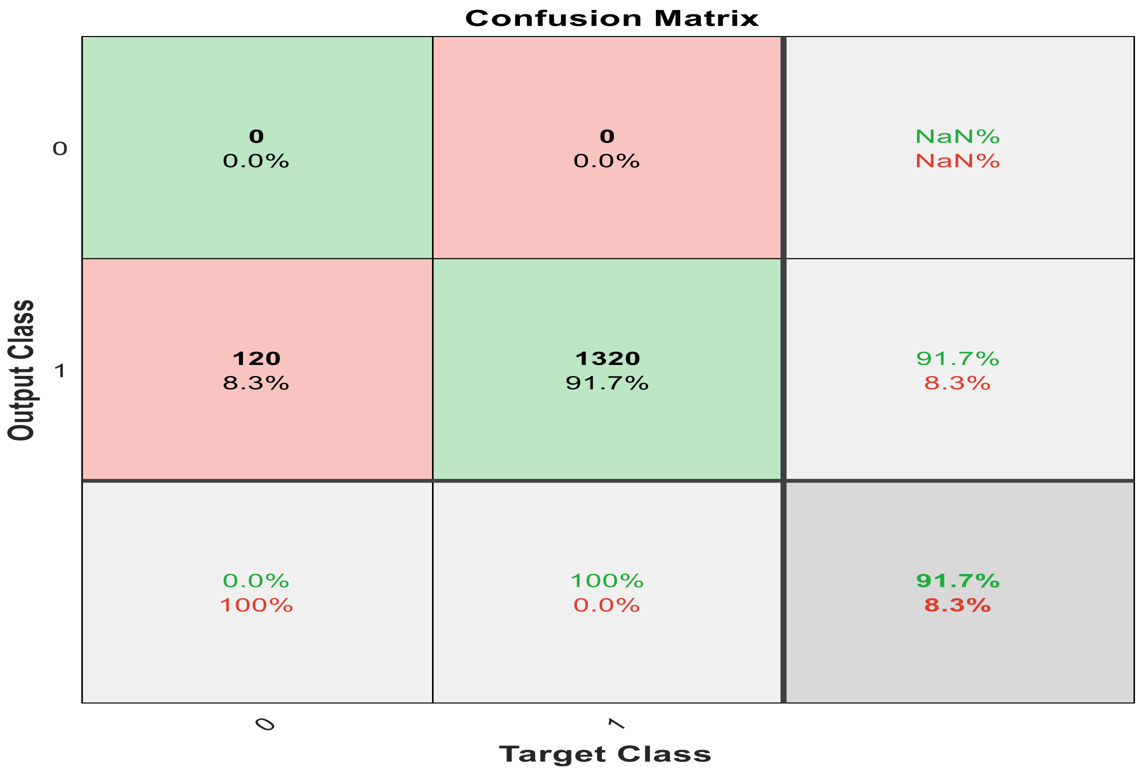

Fig 32 Confusion Plot for detection with Sgdm Optimizer

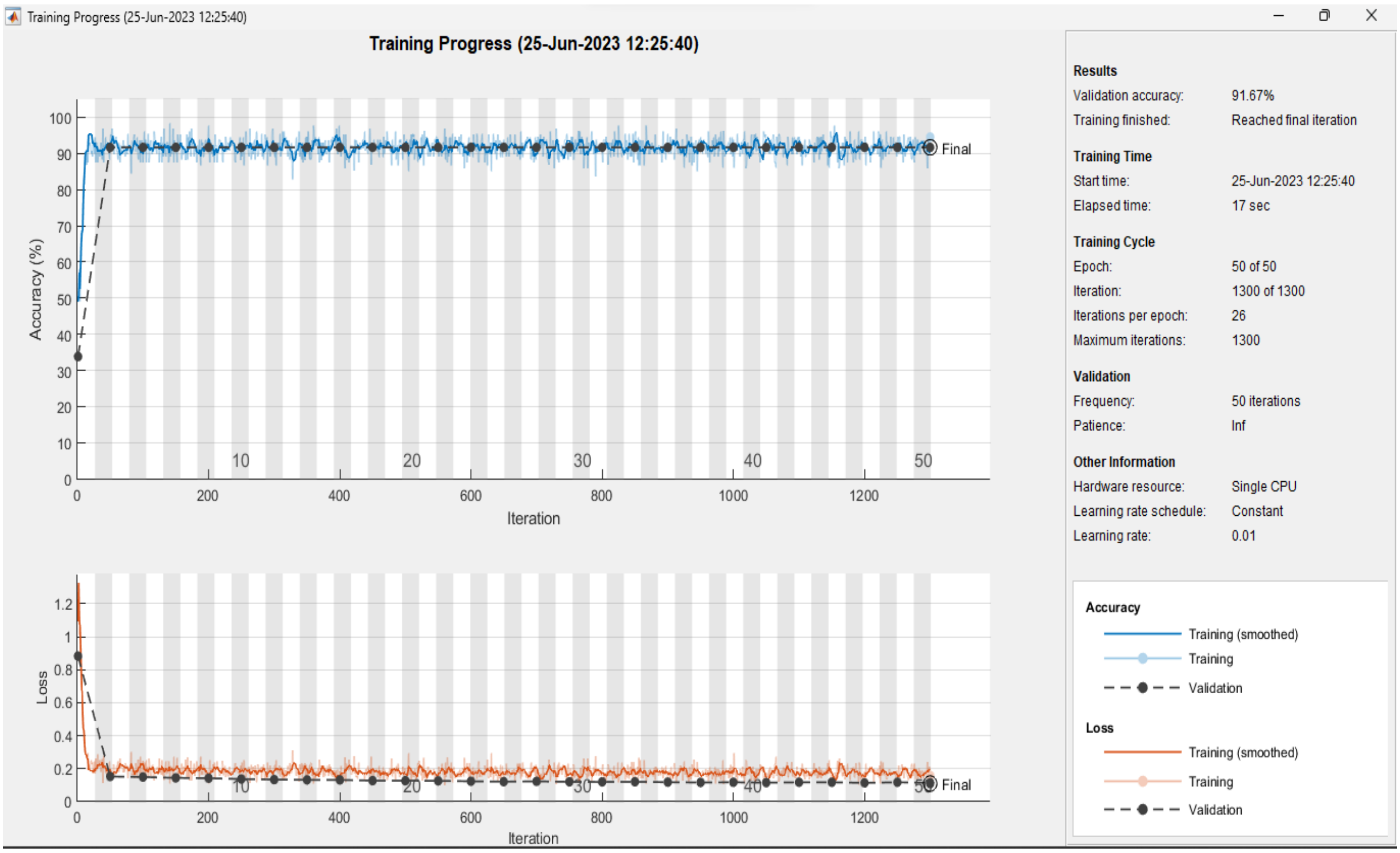

Fig 33 Training Progress Plot for detection using Sgdm Optimizer

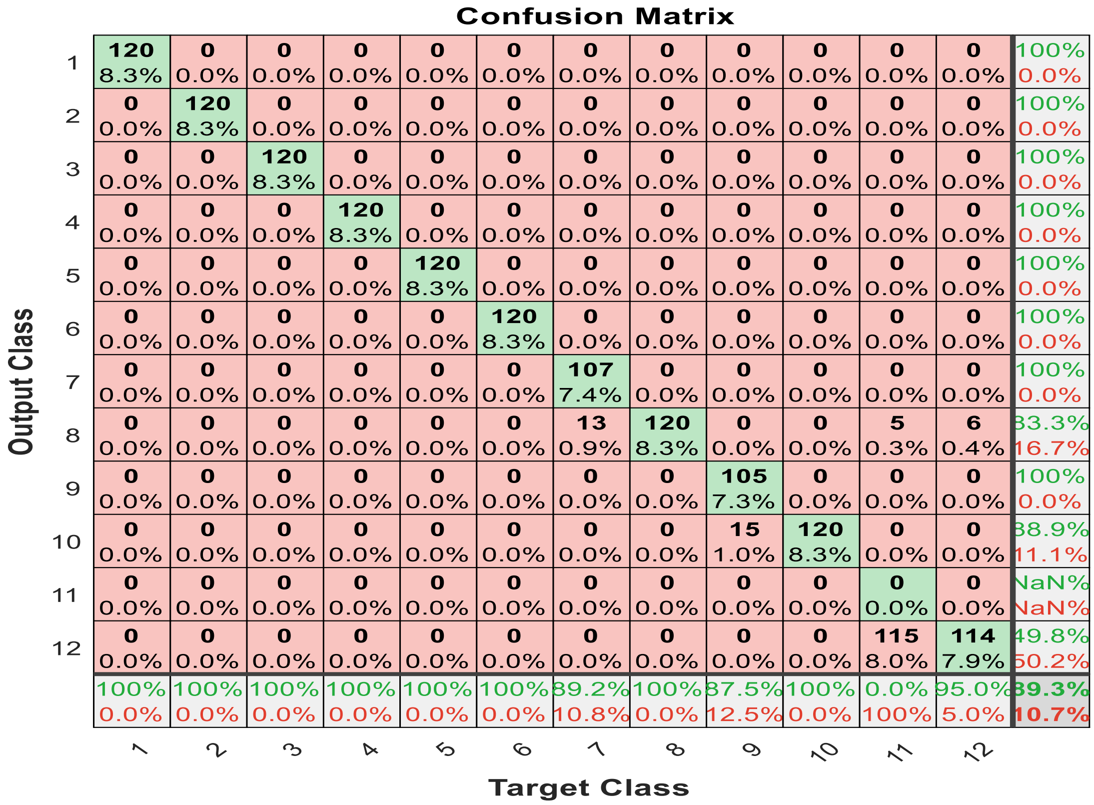

Fig 34 Confusion Plot for classification using Adam Optimizer

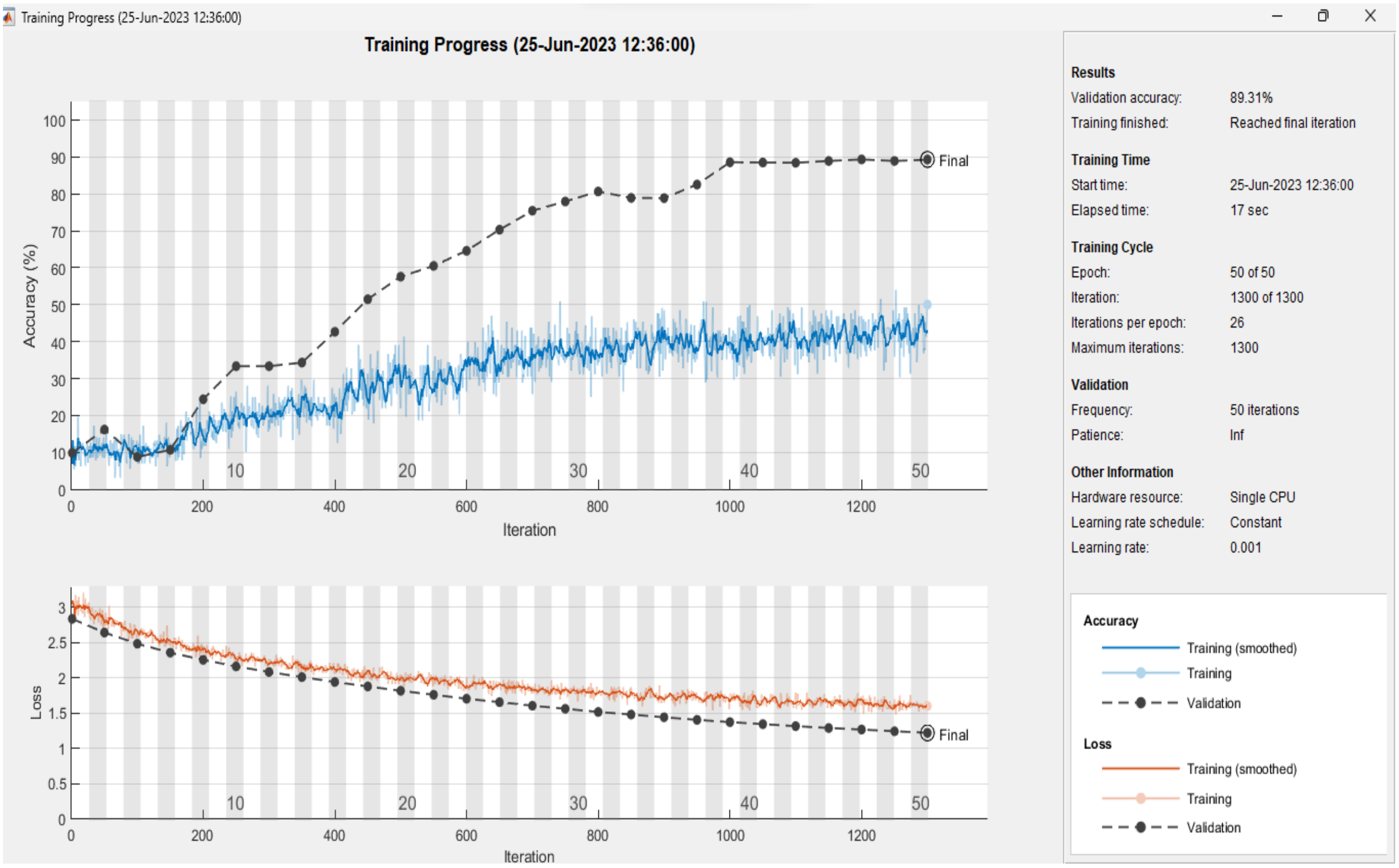

Fig 35 Training Progress plot for classification using Adam Optimizer

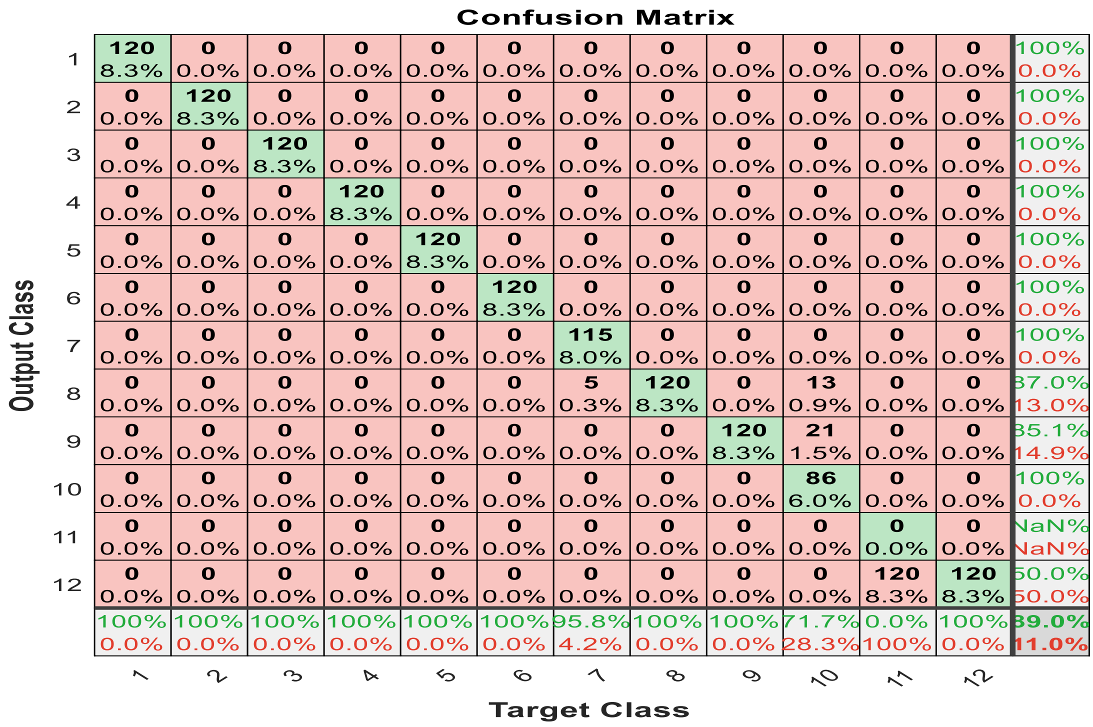

Fig 36 Confusion Plot for classification Using Sgdm Optimizer

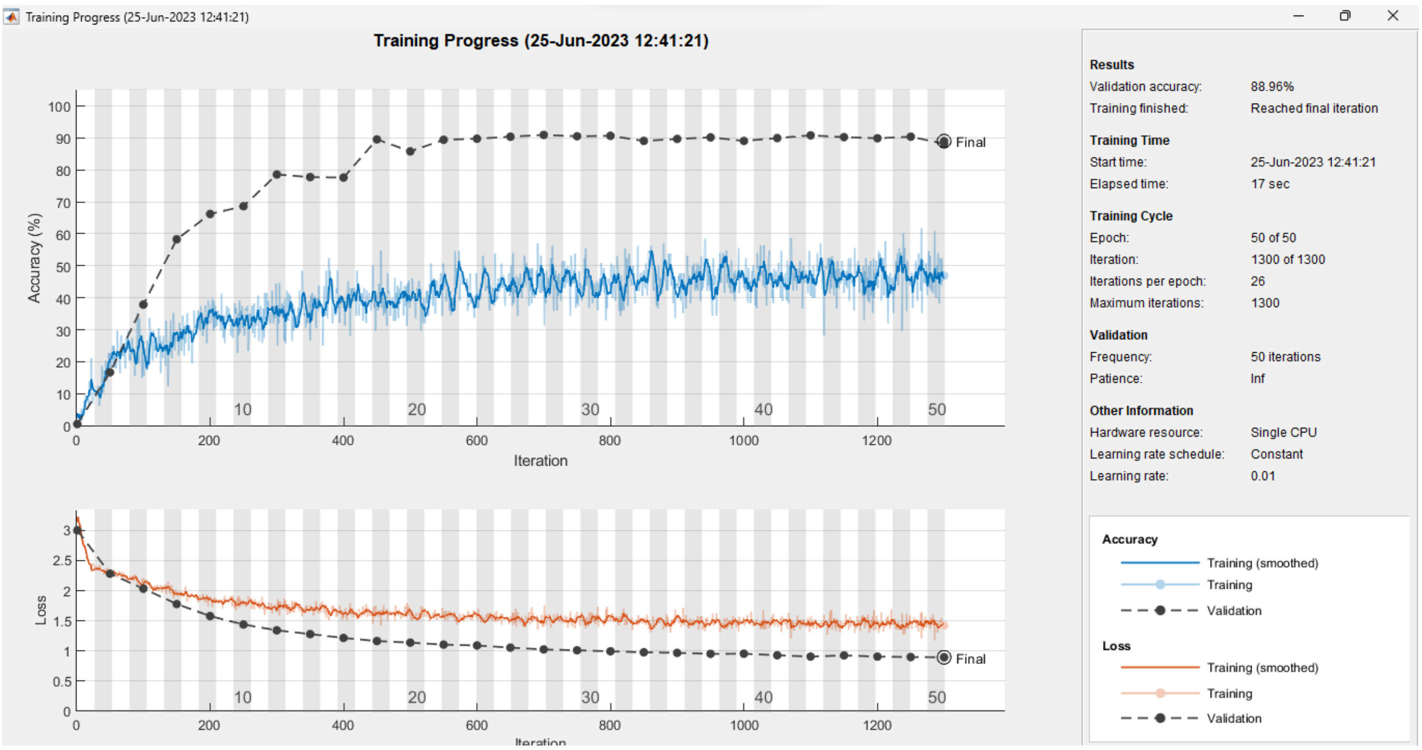

Fig 37 Training Progress Plot for Classification using Sgdm Optimiser

4.5.4 Result analysis

It is observed that CNN model with ‘Adam’ optimizer detects and classify better than ‘sgdm’ optimizer with an accuracy of 91.67 % detection and classification accuracy of 89.3% with less computational time.

4.6 LSTM

An LSTM neural network is a type of recurrent neural network (RNN) that can learn long-term dependencies between time steps of sequence data. It is introduced mainly due to RNN fail to handle the following situations-

1. It fails to store information for a longer period of time. At times, a reference to certain information stored quite a long time ago is required to predict the current output. But RNNs are absolutely incapable of handling such “long-term dependencies”.
2. There is no finer control over which part of the context needs to be carried forward and how much of the past needs to be ‘forgotten’.
3. Other issues with RNNs are exploding and vanishing gradients which occur during the training process of a network through backtracking.

Thus, Long Short-Term Memory was brought into the picture. It has been so designed that the vanishing gradient problem is almost completely removed, while the training model is left unaltered. Long-time lags in certain problems are bridged using LSTMs which also handle noise, distributed representations, and continuous values. With LSTMs, there is no need to keep a finite number of states from beforehand as required in the hidden Markov Model (HMM). LSTMs provide us with a large range of parameters such as learning rates, and input and output biases.

4.6.1 General Structure of LSTM

The basic difference between the architectures of RNNs and LSTMs is that the hidden layer of LSTM is a gated unit or gated cell. It consists of four layers that interact with one another in a way to produce the output of that cell along with the cell state. These two things are then passed onto the next hidden layer. Unlike RNNs which have got only a single neural net layer of tanh, LSTMs comprise three logistic sigmoid gates and one tanh layer. Gates have been introduced in order to limit the information that is passed through the cell. They determine which part of the information will be needed by the next cell and which part is to be discarded. The output is usually in the range of 0-1 where ‘0’ means ‘reject all’ and ‘1’ means ‘include all’.

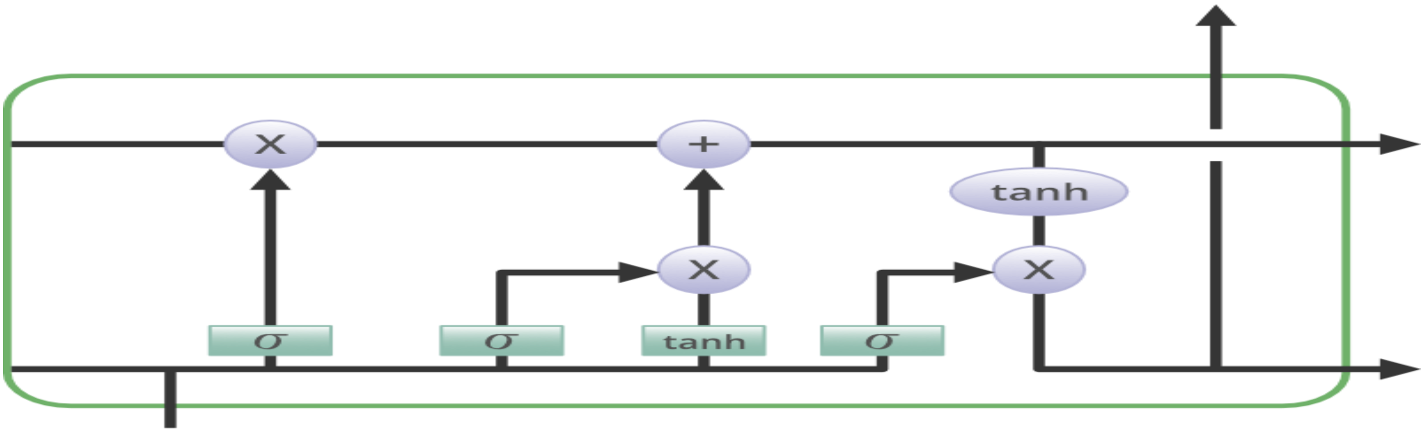

Fig 38 Basic structure of LSTM

Information is retained by the cells and the memory manipulations are done by the gates. There are three gates which are explained below:

1. Forget Gate

The information that is no longer useful in the cell state is removed with the forget gate. Two inputs x_t (input at the particular time) and h_t-1 (previous cell output) are fed to the gate and multiplied with weight matrices followed by the addition of bias. The resultant is passed through an activation function which gives a binary output. If for a particular cell state, the output is 0, the piece of information is forgotten and for output 1, the information is retained for future use.

2. Input gate

The addition of useful information to the cell state is done by the input gate. First, the information is regulated using the sigmoid function and filter the values to be remembered similar to the forget gate using inputs h_t-1 and x_t. Then, a vector is created using the tanh function that gives an output from -1 to +1, which contains all the possible values from h_t-1 and x_t. At last, the values of the vector and the regulated values are multiplied to obtain useful information.

3. Output gate

The task of extracting useful information from the current cell state to be presented as output is done by the output gate. First, a vector is generated by applying the tanh function on the cell. Then, the information is regulated using the sigmoid function and filtered by the values to be remembered using inputs h_t-1 and x_t. At last, the values of the vector and the regulated values are multiplied to be sent as an output and input to the next cell.

4.6.2 Designing of LSTM model

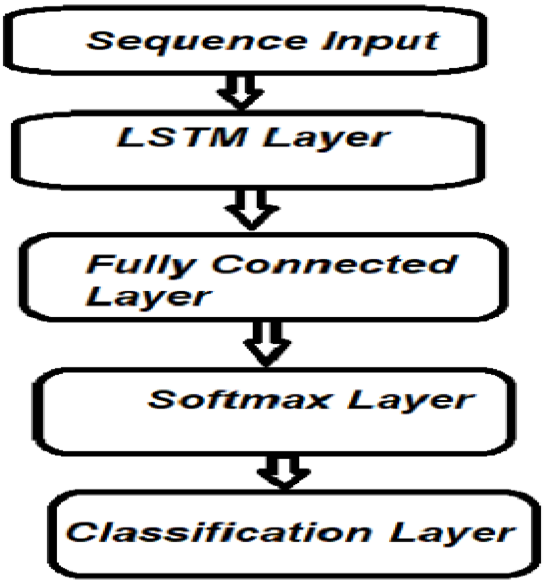

Fig 39 LSTM Architecture of Proposed Model

The proposed LSTM model for fault detection and classification process consist of five layers. First layer is sequence input and number of sequences are based on the number of input signals. The second layer is LSTM layer, the number of hidden layers is 100. Hidden layer consists of memory cells and related gate units. The third layer, a fully connected layer, was set to the same size as the combination of both fault and no-fault conditions equal to 12 for this study for classification and 2 for detection. A SoftMax layer added next to a fully connected layer for potential prediction and SoftMax output classifies input sequence data of each fault type and last layer predict the fault class as output.

4.6.3 Performance analysis of LSTM Model

Table 14 Hyperparameters for detection &classification LSTM models

Hyper Parameters	**Detection**		**Classification**	
Epoch	50		50	
No of Features	6		6	
No of Classes	2		12	
No of Layers	5		5	
Training Options	Adam Optimizer	Sgdm Optimizer	Adam Optimizer	Sgdm Optimizer
Accuracy in %	91.67	99.93	90.06	99.94
Computation Time	47.338522	45.499966	44.449654	40.070506

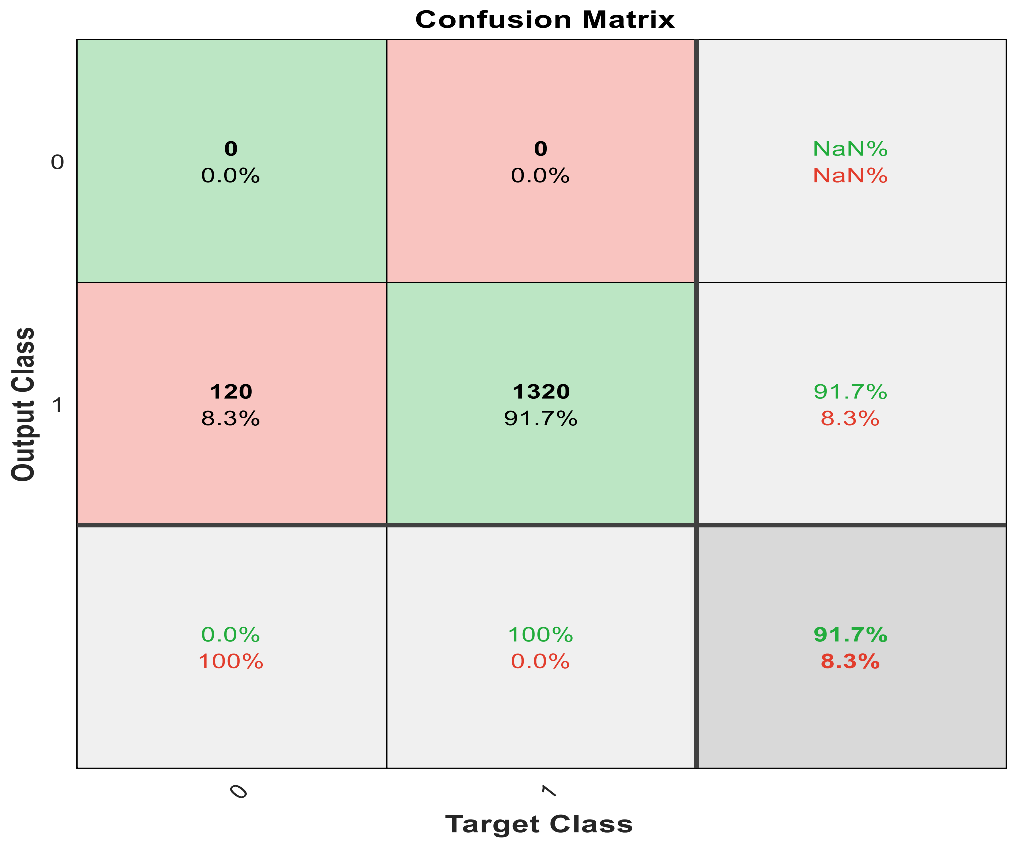

Fig 40 Confusion Plot of Detection using Adam Optimizer

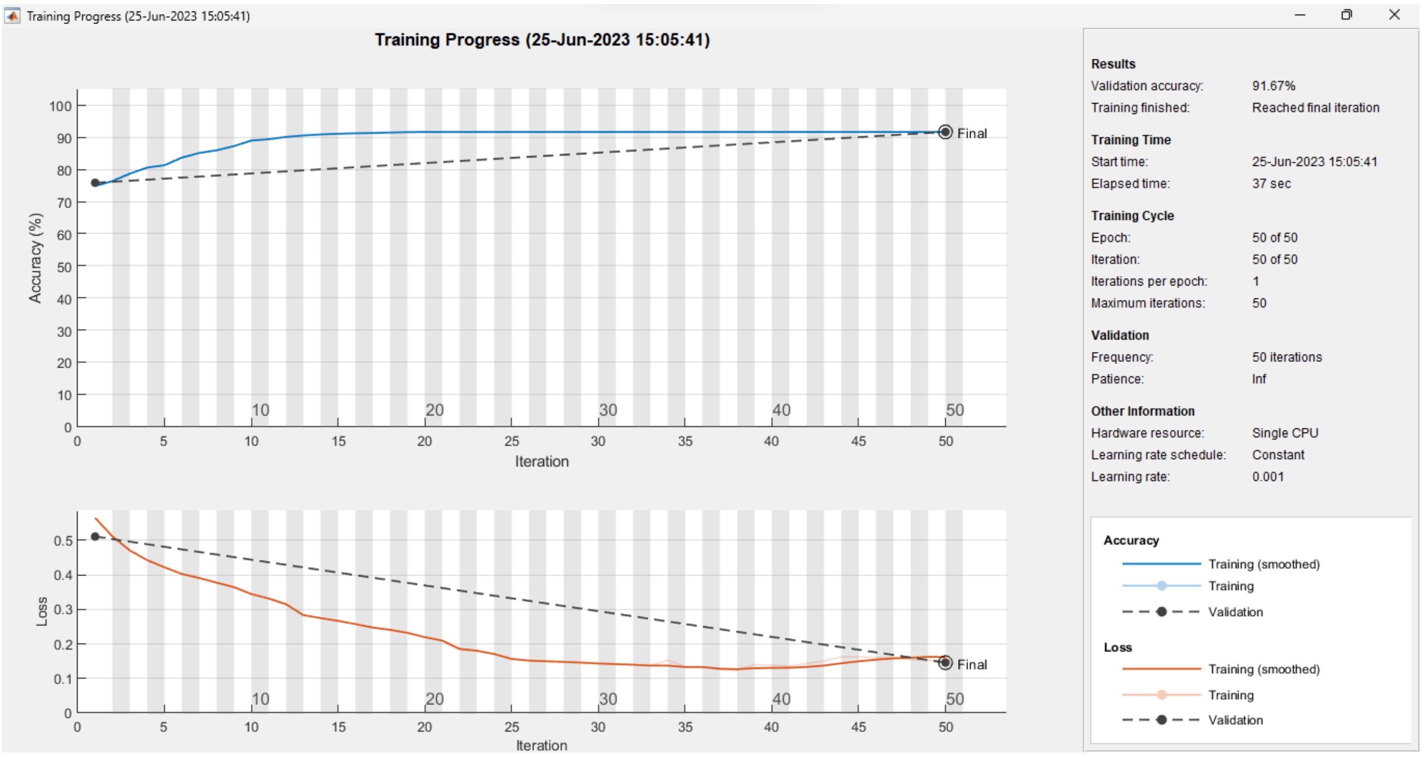

Fig 41 Training Progress Plot for detection Adam Optimizer

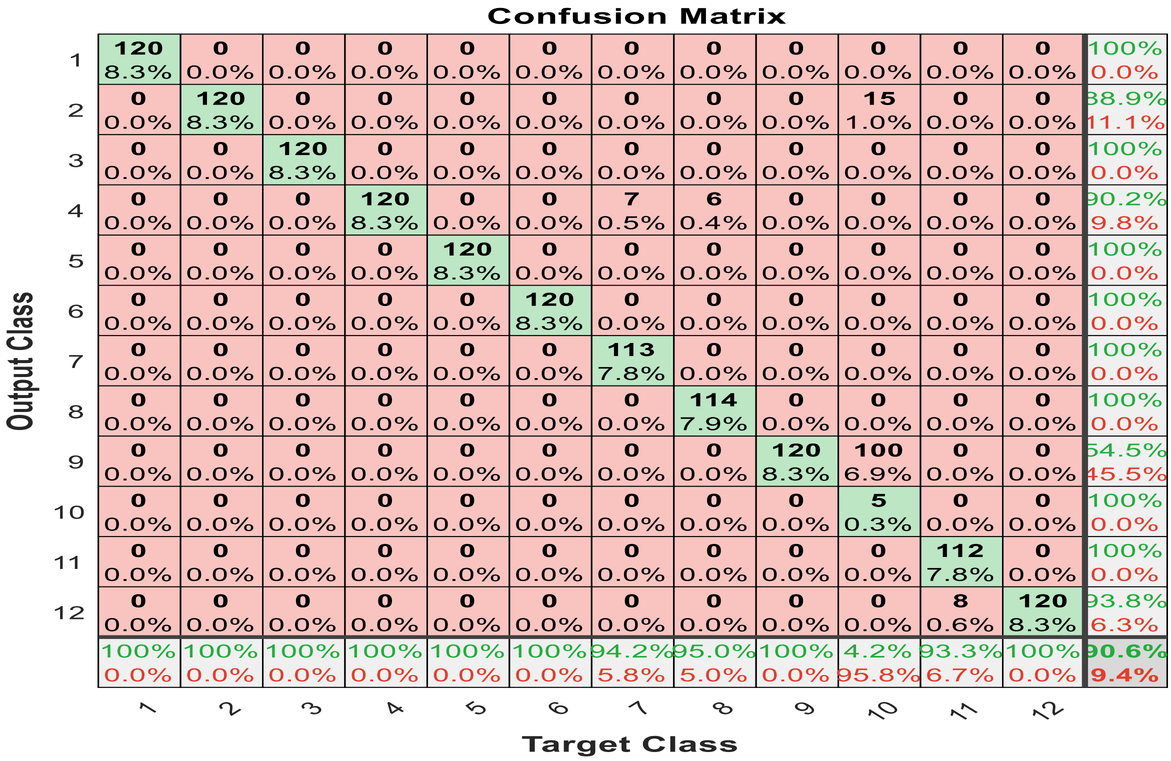

Fig 42 Confusion Plot for Classification using Adam Optimizer

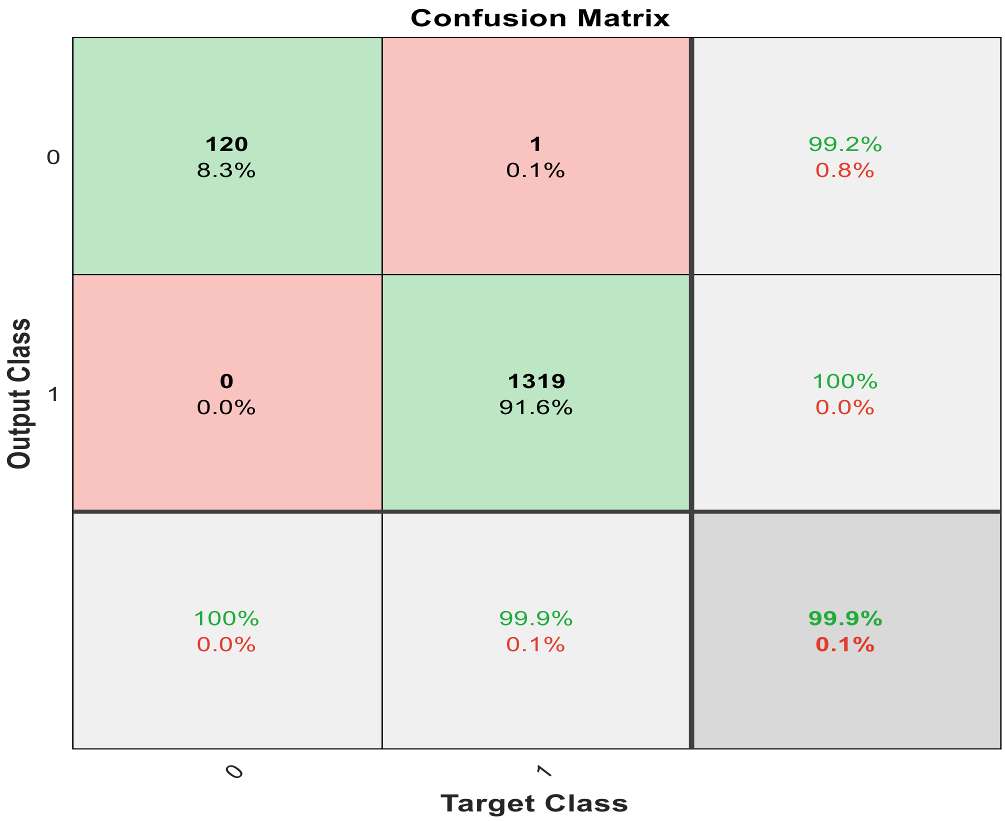

Fig 43 Confusion Plot for detection using Sgdm optimizer

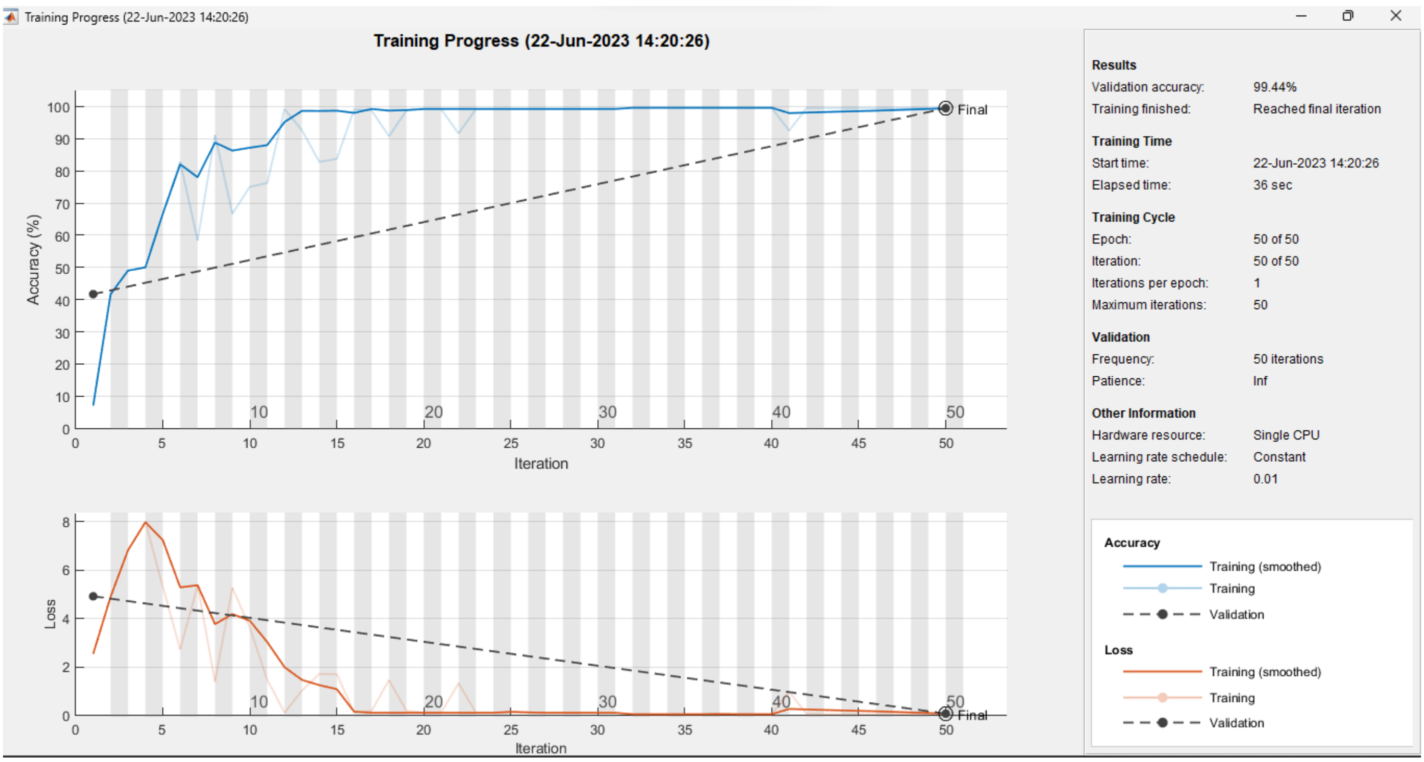

Fig 44 Training progress plot for classification using sgdm optimizer

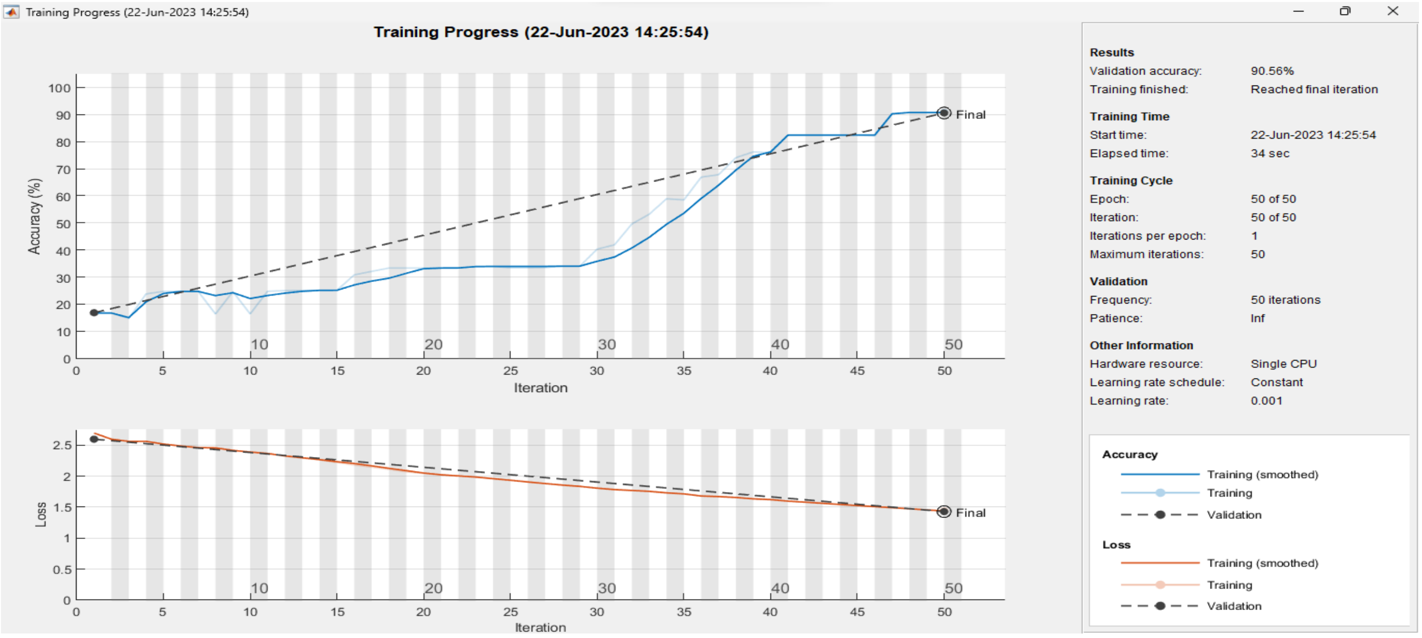

Fig 45 Training Plot for Classification using Adam Optimizer

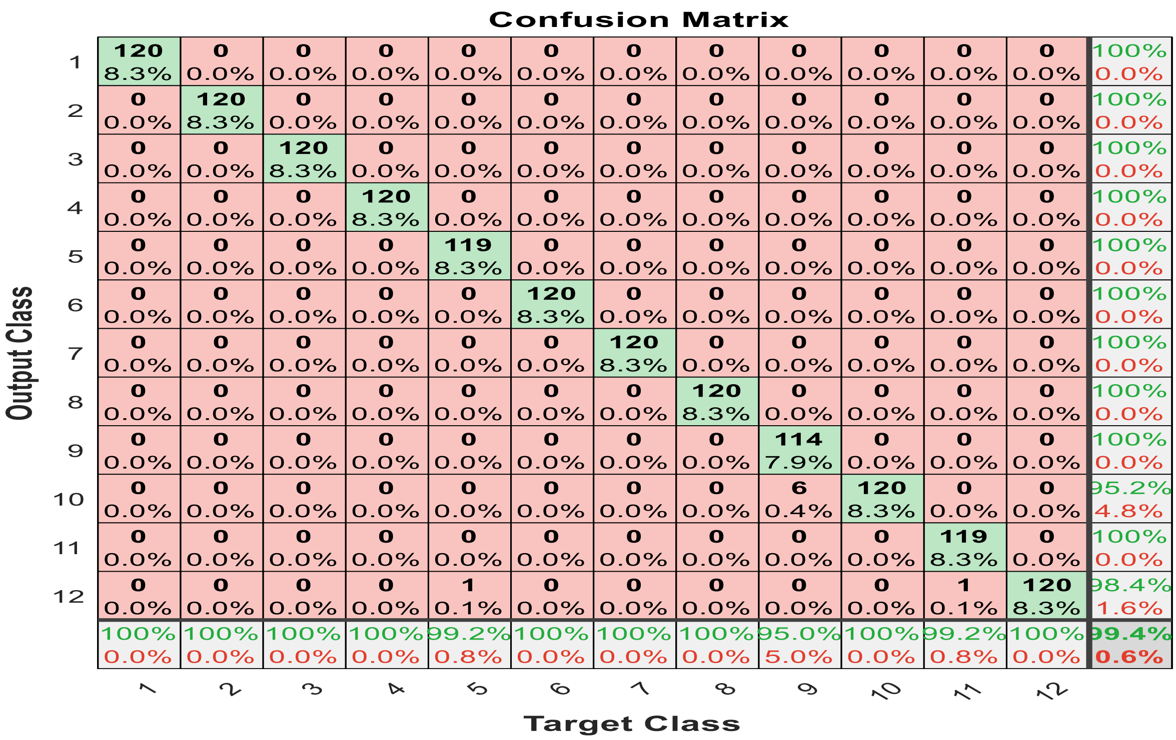

Fig 46 Confusion Plot for Detection using Sgdm optimizer

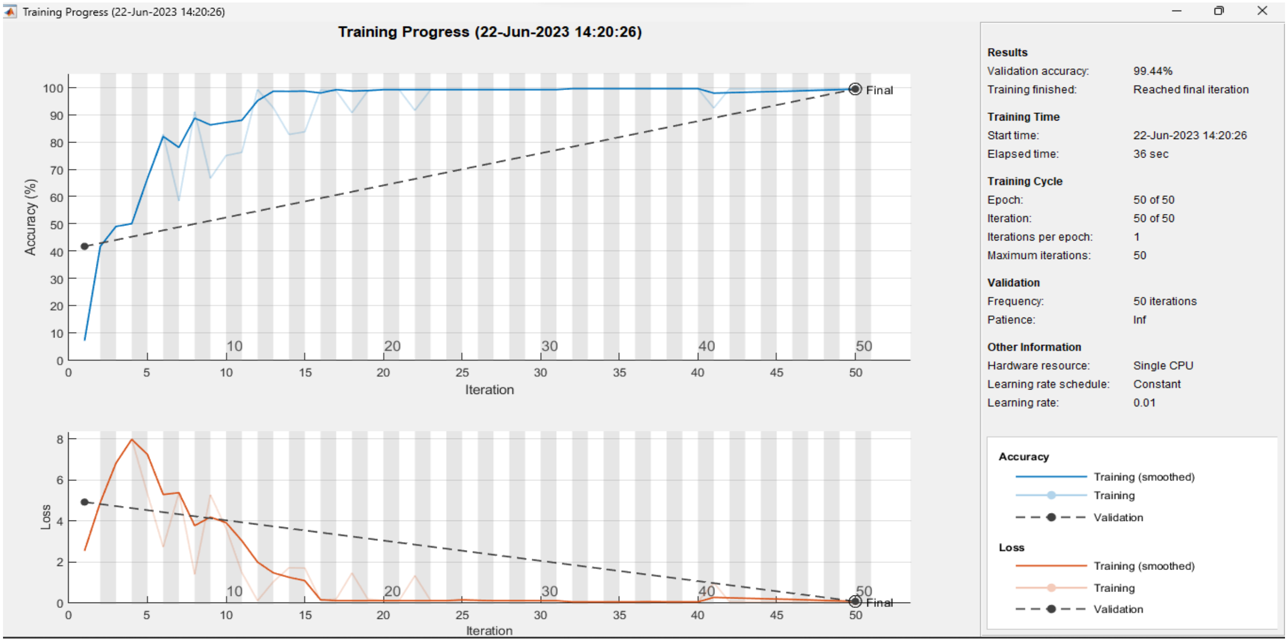

Fig 47 Training Progress Plot for Classification using Sgdm Optimizer

4.6.4 Result analysis

It is observed that proposed LSTM model with 'sgdm' optimizer gives optimal results for detecting and classifying of faults with an accuracy of 99.93 % detection and classification accuracy of 99.94% with less computational time as compared to model with 'Adam' optimizer.

4.7 Comparative Performance study of various Algorithms

Table 15 Performance comparison of various algorithms

Algorithm	Detection		Classification	
	Accuracy in %	Computation Time in seconds	Accuracy in %	Computation Time in seconds
ANN (trainlm)	98.91	4.321098	99.82	10.541782
CNN (Adam)	91.67	18.983302	89.3	21.33
LSTM (Sgdm)	99.93	45.499966	99.94	40.070506

Performance comparison of three algorithms namely ANN, CNN, and LSTM is made on the basis of accuracy and computational. The following points are concluded-

- LSTM models perform better than others model with higher detection accuracy of 99.93% and classification accuracy of 99.94%.
- Deep learning gives better accuracy however it takes longer computational time.
- CNN performance can be increase by increasing the number of layers and size of data input.

CHAPTER 5: CONCLUSION

This project employs shallow neural network (ANN) and deep neural network (CNN, LSTM) for detection and classification of transmission line faults. It is conducted in two phases, in the first phase a short transmission line of 55km is considered. Simulink model is developed using MATLAB Software, three phase RMS voltage and current at the sending end are collected as fault dataset. These datasets are used to train ANN (shallow network) model. It is found that ANN can accurately detect, classify and locate faults. In the second phase, a medium transmission line is considered to generate the fault dataset. Detection and classification of three different algorithm (ANN, CNN, LSTM) is performed at 50 epochs. And a comparison of these algorithms is made on the basis of accuracies and computational time. From this study, it can be concluded that, deep learning-based techniques LSTM performs better with a detection accuracy of 99.3% and classification accuracy of 99.4% than other algorithms used in this study. Also, it is observed that better results were given when ANN trained with 'trainlm', CNN trained with 'Adam' training option and LSTM trained with 'sgdm' training option. In the future, suggested model performances should be evaluated from real time recorded fault data from real Power energy system.

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