International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8298
***Article Received:** 08 July 2023 **Revised:** 27 August 2023 **Accepted:** 18 September 2023*

Evaluation of Transfer Learning Techniques for Fault Classification in Radial Distribution Systems: A Comparative Study

Garima Tiwari[1], Sanju Saini[2]
[1]EED Deenbandhu Chhoturam University of Sci. and Technology
Murthal, Sonipat, Haryana, 131039
e-mail: 18001902001garima@dcrustm.org
[2]EED Deenbandhu Chhoturam University of Sci. and Technology
Murthal, Sonipat, Haryana, 131039
e-mail: sanjusaini.ee@dcrustm.org

Abstract— Transfer learning has recently had a detectable impact on the state of the art in a wide variety of applications, and this trend is expected to continue in the near future. Both transfer learning and deep learning algorithms make use of a number of network layers, each of which may be intellectually learned and typically represents the data in a hierarchical fashion with increasing levels of abstraction. Convolutional neural networks have been proven to be exceptionally successful machine learning and deep learning techniques for a number of computer vision problems. These networks were developed by companies such as Alexa, Google, and Squeeze. Fault diagnostic strategies that are based on deep learning techniques are currently a topic of intense investigation due to their higher performance. Using transfer learning technology to carry out fault categorization in a power distribution system in a manner that is both accurate and efficient The work at hand employs a fault classification model for a radial power distribution system that is based on transfer learning and deep learning. Images of time series of three-phase fault currents are acquired via simulation with the assistance of PSCAD software as part of the proposed approach for doing so. In the next step, CNN models that are based on Alex Net, Google Net, and Squeeze Net are utilized to extract fault features from defective photos in order to categorize eleven distinct defects (using the MATLAB platform). For the categorization of defects in a radial distribution system, Alex Net, Google Net, and SqueezNet each offer accuracy of approximately 98.92%, 97.48%, and 99.82%, respectively. In this study, the classification of faults in a distribution system is accomplished with the help of AlexNet, GoogleNet, and SqueezNet. According to the findings of the simulations, the test accuracy for SqueezeNet is the highest it can be, coming in at 99.82%. Because of this, selecting it as the solution to the issue of fault classification in the test distribution system is your best option.

Keywords- Transfer learning; Fault classification; Distribution System.

I. INTRODUCTION

Power-dissipating short-circuit faults are a constant hazard to distribution systems. In order to complete a rapid restoration, it is essential to quickly and accurately identify and resolve any issues that may arise. Due to the structural challenges of distribution grids, such as non-homogeneity and the presence of laterals, fault identification methodologies employed in transmission grids cannot be applied directly to distribution grids [1]. Numerous studies [2–20] have accounted for the unpredictability of distribution systems by employing machine learning-based fault diagnosis methods employing data-based knowledge corresponding to varying conditions. Object recognition, visual object/speech recognition, and other fields such as genomics have all benefited significantly from deep learning [21]. CNNs belong to the class of deep learning algorithms [22]. It obtains favourable image recognition and classification results. Deep learning (DL) processes can automatically extract illustrative features from unprocessed signal data, mitigating the influence of artificial learning experiences [21, 22]. These DL-based methods outperform conventional machine learning techniques by overcoming their limitations [23] and producing superior results. Alexnet,

Googlenet and SqueezeNet are CNN models that have been pre-trained and have produced outstanding results in recent years [24]. These models have a significant impact on image recognition and classification tasks due to their exceptional performance. Numerous studies [25–28] have used deep learning algorithms for fault diagnosis in shipyard power systems.

In this study, a deep learning structure is developed for defect classification in an IEEE 13-node radial feeder power distribution system (4.2 version) simulated by PSCAD. The novel aspect of this work is that it uses a time series of three-phase fault currents to monitor the distribution system's condition. The CNN models Alexnet, Googlenet, and SqueezeNet (transfer learning approach) are used to extract fault features and fault classification. This study examines and

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8298
***Article Received:** 08 July 2023 **Revised:** 27 August 2023 **Accepted:** 18 September 2023*

compares the classification accuracy of Alexnet, Googlenet, and Squeezenet for various power distribution system faults. In the remainder of this paper, Section 2 introduces the case study of the IEEE 13-node radial distribution system and CNNs such as AlexNet, GoogleNet, and SqueezeNet. Section 3 describes the methodology employed. The 4th and 5th sections present the results and conclusion.

II. TYPE BACKGROUND THEORY

In this work, an IEEE 13-node distribution test feeder (as shown in Fig. 1) with a 115 KV voltage source is modelled and simulated in the PSCAD software for creation of data (to train and test).

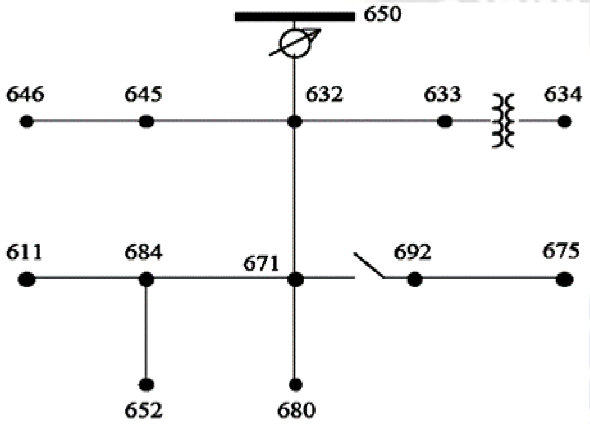


Figure 1. Single Line Diagram of IEEE-13 Node Feeder

In the subsections below, three CNN architectures used in this work are described.

A. AlexNet

In the year 2012, Alex Net was suggested by “Alex Krizhevsky”, “Ilya Sutskever”, & “Geoffrey Hinton".It’s architecture comprises 25 layers with three fully-connected and five convolutional layers. In this architecture, ReLU activation is used. The input RGB images for AlexNet are of the size 227 × 227 × 3. As depicted in Figure 2, convolution and maximum pooling is performed in the first convolutional layer using 96 various 11×11-size receptive filters (LRN). To conduct the most pooling operations, three filters are used. 55 filters are used in second layer to perform the identical procedures. 3rd to 5th convolutional layers utilize 384, 384, and 296 feature maps. Dropout uses 2 fully-connected layers first, then a Softmax layer. Two networks are simultaneously trained for this model, each of which have the same amount of feature maps and comparable structural similarities [23].

B. GoogleNet

The GoogLeNet is a model submitted by Google's Christian Szegedy to decrease computing complexity compared to classical CNN. The proposed solution involved incorporating “Inception Layers” with varied receptive fields formed by various kernel sizes as shown in Fig. 3. GoogLeNet has a total of 22 layers which is significantly high, but, compared to AlexNet's 60 million network parameters, it has only 7 million, i.e., it uses a lot less network parameters. Moreover, Google Net’s computations were likewise 1.53G MACs, much lower than AlexNet [23].

C. SqueezNet

Smaller DNN designs have at least three advantages over larger DNN systems with similar accuracy:

1. They require less bandwidth
2. Whenever a new model is transferred from the cloud to an autonomous vehicle, they require less server connectivity during distributed training
3. Installation of smaller DNNs on FPGAs as well as other memory-constrained hardware is simpler.

SqueezeNet, a compact DNN architecture, was presented [24] to attain these advantages. With 50 times less parameters, it can achieve AlexNet-level accuracy on ImageNet. As seen in Fig. 4, 18 convolutional neural layers make up SqueezeNet [24]. The network can classify images into 1000 different object categories after training, including a variety of animals. The network is having ability to learn detailed feature's representations for a variety of photos as a result.

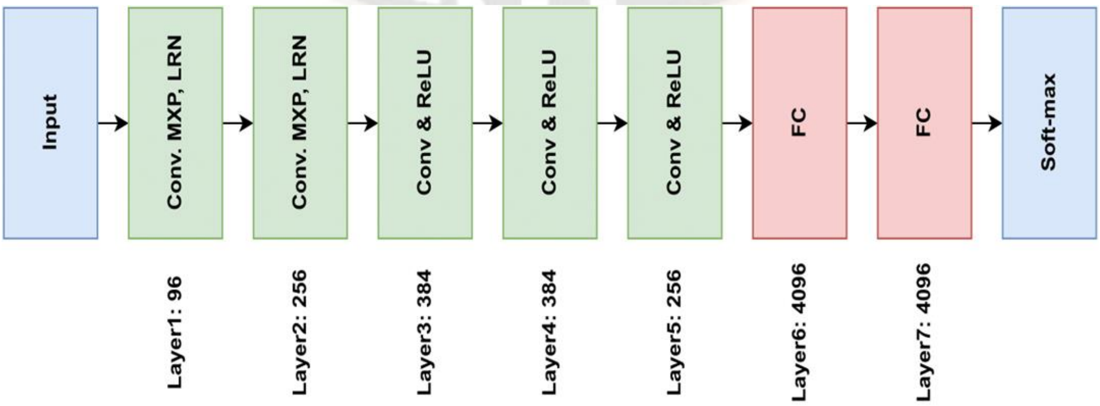


Figure 2. Architecture of Alex Net [23]

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8298
***Article Received:** 08 July 2023 **Revised:** 27 August 2023 **Accepted:** 18 September 2023*

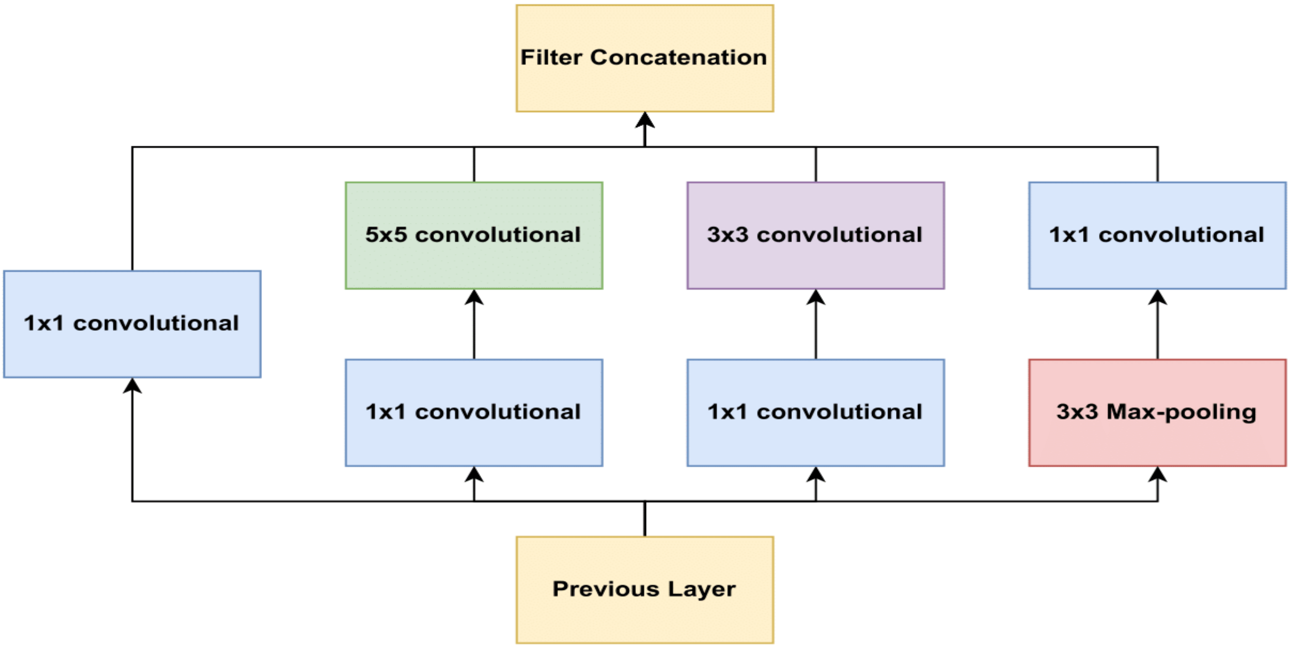


Figure 3. Feeder Inception layer with dimension reduction [23]

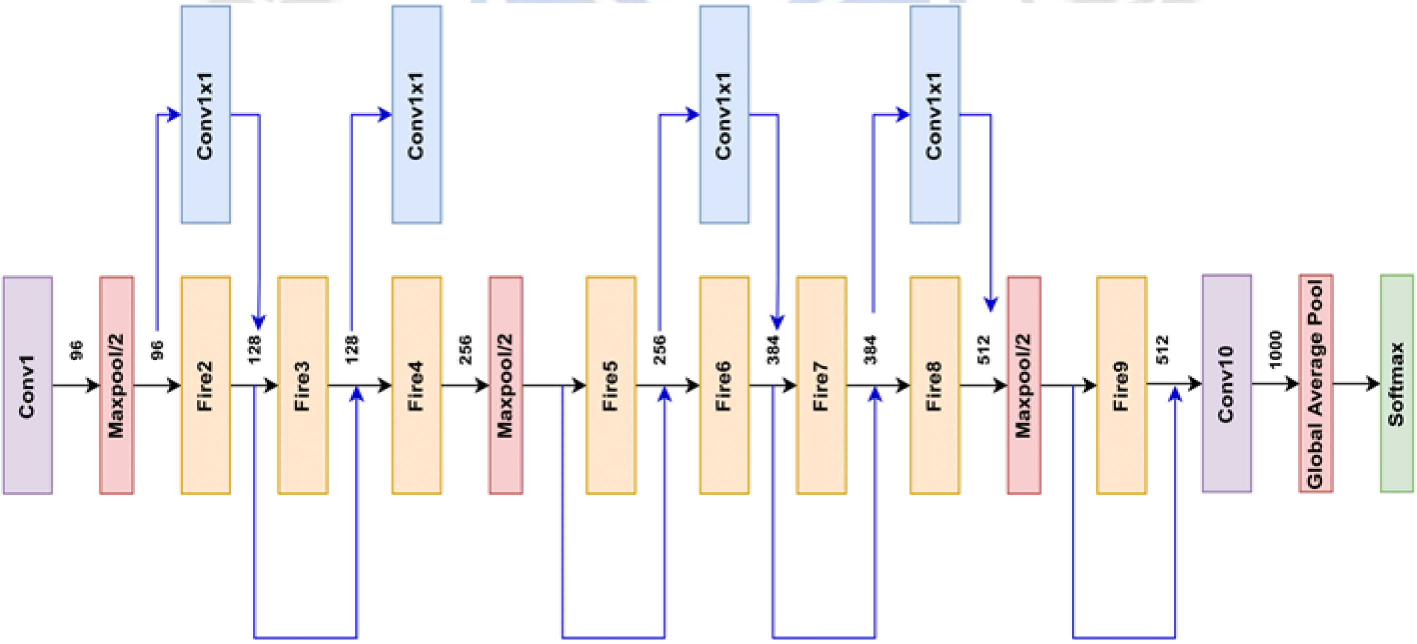


Figure 4. Architecture of Squeeze Net [24]

III. RESEARCH METHODOLOGY

The overall flow of work is represented in Fig.5. Involves the collection of fault current time series data via simulation of a 13-node distribution system in PSCAD. Then this data is exported to MATLAB, thus creating images to serve as input data for CNN. Target data for training CNN consists of labels for fault types. Using this input-output data, three Convolution Neural networks, i.e., ALEXNet, GoogleNet, and Squeezenet are trained and tested for fault classification accuracy. Details are given in the following subsections.

A. Collection of fault current values and creation of Training Data

In transmission and distribution systems, there are five separate fault types: L-G fault, L-L fault, L-L-G fault, L-L-L

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8298
***Article Received:** 08 July 2023 **Revised:** 27 August 2023 **Accepted:** 18 September 2023*

fault, and L-L-L-G fault (11 fault cases total for 3 lines). In this study, 3phase currents under all fault types are recorded under the various situations listed in Table 1. In the PSCAD/EMTDC environment, a simulation model is set up for this purpose. This model's simulation run lasts for 1.3 seconds, and the failure occurs between 0.05 and 0.1 seconds. As a result, there are a total of 5568 cases [5120(8nodes*8resistaces*8inception angles) cases for every 10 types of fault and 448(8nodes*7resistances *8inception angles) cases for ABC fault] for which the time series of the 3 phase current during each fault are measured, and the samples are arranged to create a vector with 5568 rows for the training of CNN. For training reasons, MATLAB imports these numbers of fault situations. A label representing the input data's fault kind makes up the output training data.

B. Transfer learning

A representative deep learning technique, CNN is a feed-forward neural network with a deep structure. One crucial aspect of CNN is its local receptive field [21]. The convolutional, pooling, and fully connected layers are the three network layer architectures that make up the majority of the whole CNN model. The feature map of the image is obtained by the convolutional layer using a variety of filters. Due to the pooling layer's usage of downsampling, which lessens the number of model parameters, over-fitting is somewhat prevented. Following a series of convolutional-pooling layers, the completely linked layer completes the classification process finally [22].

Transfer learning, which is frequently applied in deep learning applications, starts by learning a new task using a pretrained Convolutional Neural network (CNN). These pre-trained networks can categorize images into 1000 different item categories. For a variety of images, these networks learn rich feature representations. Fine-tuning these networks is typically quicker and simpler. With fewer training images, learned features may be applied to a new assignment fast. After receiving a picture as input, the network returns a label for each [22]. As previously mentioned, three types of pretrained convolutional neural networks—Alex Net, Google Net, and SqueezeNet—are used in the current work to classify different fault types. by doing the actions outlined below:

i. Loading the data
ii. Loading the Pretrained Network
iii. Replacing the Final Layers
iv. Freezing the Initial Layers
v. Training the Network
vi. Classifying the Validation Images

The faults' input (images)-output (labels) data is first split into training and validation data (80% and the remaining 20%). A pretrained network loads the transfer learning Architecture in the second stage, which includes GoogleNet, SqueezeNet, and AlexNet. In the third stage, the final three layers are swapped out for the fully-connected layers, which include a classification output layer and a softmax layer. It is optionally feasible to freeze the weights of networks' prior layers by setting their learning rates to "0" during training. As a result, Network training is significantly sped up because the frozen layers' gradient need not be calculated. Earlier network layers can avoid overfitting to the new data set by being frozen. The network is then trained using training data in MATLAB, and testing data is used to evaluate the network's classification accuracy.

C. Classification Accuracy

We have presented the testing data to evaluate the effectiveness of each strategy, and labels are checked for the percent of accurate predictions to assess accuracy in accordance with Equation 1.

$$\text{Accuracy} = (\text{Ncorrect}/\text{Ntotal})*100\% \quad (1)$$

Here, Ncorrect is the total number of correctly classified trials, and Ntotal is the overall trials in the test dataset.

D. Kappa Score

Another performance metric utilized to assess the effectiveness of our strategy is the kappa score. It is regarded as a statistically reliable indicator of the method's effectiveness [25]. The kappa score typically ranges from 1 to -1, with a positive result of 1 denoting perfect categorization. The kappa values we discovered are calculated by eqn. 2.

$$K = \frac{Acc-Racc}{1-Racc} \quad (2)$$

Here, Acc denotes the obtained accuracy whereas Racc denotes random accuracy. Eqn. 3 represents how random accuracy is calculated'

$$Racc = 1/N \quad (3)$$

Here, 'N' represent total classes.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8298
***Article Received:** 08 July 2023 **Revised:** 27 August 2023 **Accepted:** 18 September 2023*

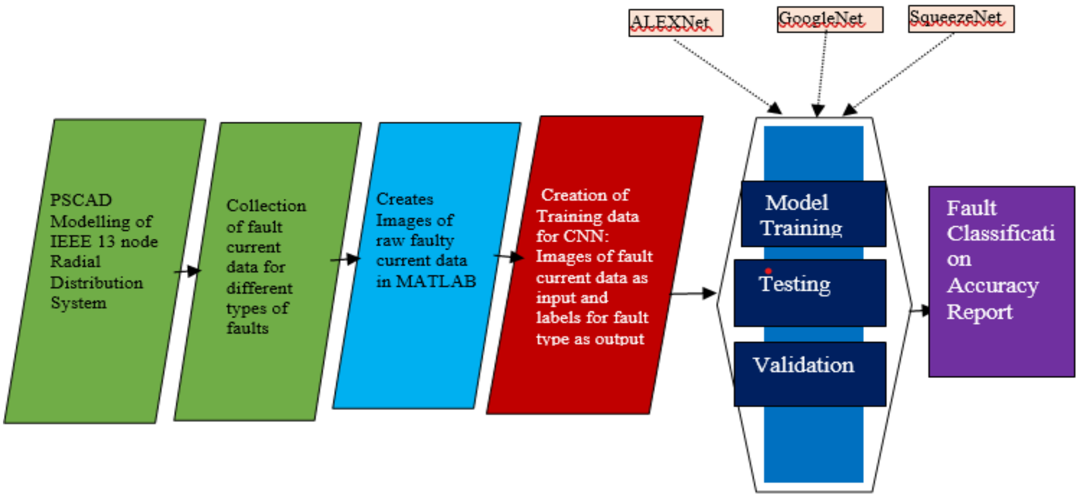
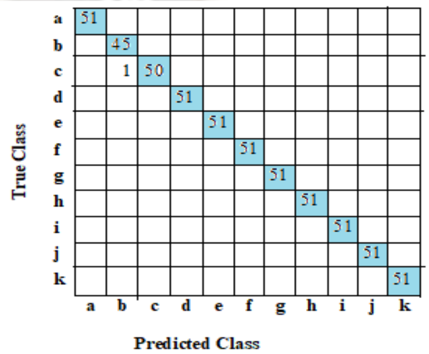
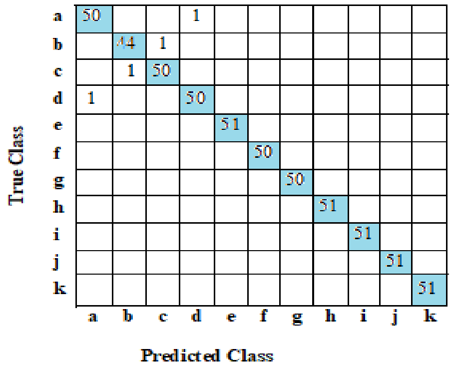


Figure 5. Flow Chart of Research Methodology

IV. SIMULATION RESULTS AND DISCUSSION

This work develops a PSCAD Simulink model of the IEEE 13 bus test distribution system with the ability to generate eleven different fault types at eight different nodes, namely nodes (Figure 1) with the numbers 632, 633, 634, 650, 671, 675, 680, and 692 as given in Table 1. There is an option to simulate every type of fault for a variety of fault resistance and fault inception angle values. Using MATLAB 2021, images of time series of three-phase fault currents are created as training data for CNN.





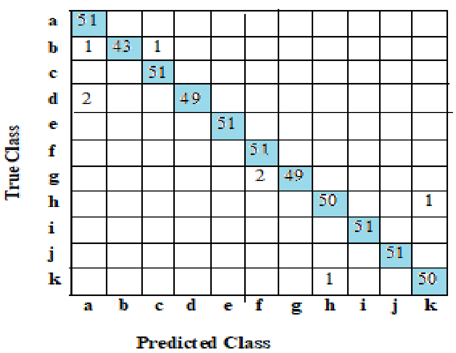


Figure 6. . Confusion Matrix: a) Alexnet, b) Google Net, c) SqueezeNet

TABLE I. DIFFERENT FAULT CONDITIONS FOR TRAINING

Parameter	Value
A faulted node of model	632,633,634,650 671,675,680,692 nodes
Fault inception angles	10,35,60,85,110,135,160,185 degree
Fault resistances	0,0.5,50,100,500,1000,1500 ohm

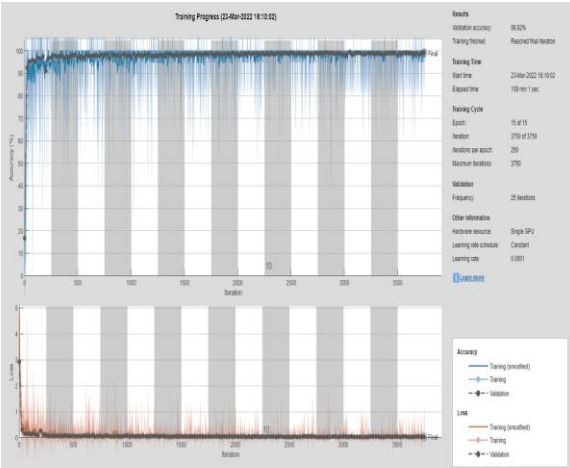
The whole data consists of labels for the associated fault category as well as 5568 photos of the fault current time series as input. As well as pre-processing chores like scaling, rotation, and reflection, batches of training data (3898 photos), validation data (1115 images), and test and prediction data (555 images) are also prepared. Images are downsized to be consistent with the deep learning network's input scale. In order to avoid the network from becoming overfitting, image data is supplemented using randomized pre-processing techniques.

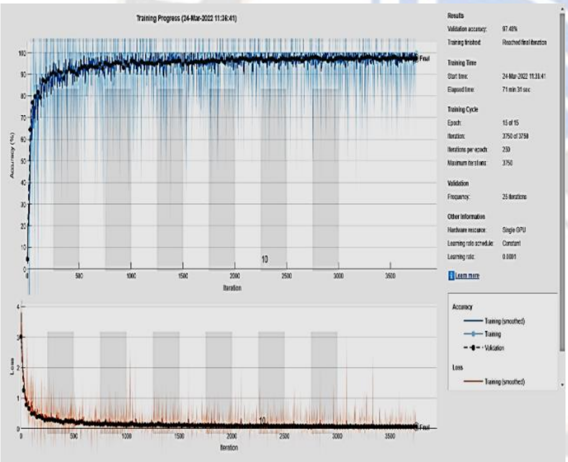
Then, AlexNet, Google Net & SqueezNet are used as transfer learning models. The size of the input image, Maximum number of epochs, iterations, and training time for each is represented in Table 2. Confusion Matrix (for test data) and Training progress is represented in Figs. 6(a-c) and 7(a-c) respectively. In confusion matrices, classes a to k represent A-B, A-B-C, A-B-C-G, A-B-G, A-G, B-C, B-C-G, B-G, C-A, C-A-G, and C-G short circuit faults respectively.

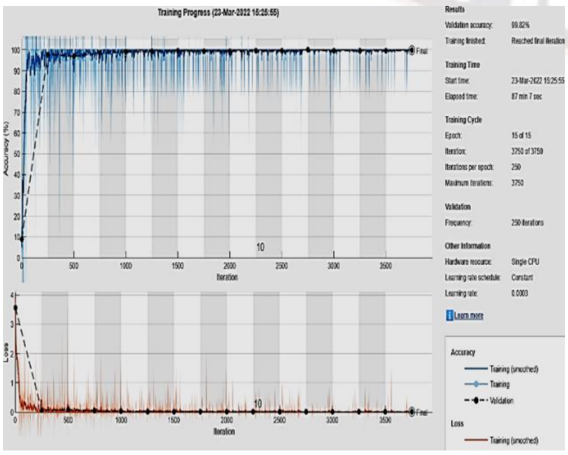
International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8298
***Article Received:** 08 July 2023 **Revised:** 27 August 2023 **Accepted:** 18 September 2023*

TABLE II. TRAINING PARAMETERS COMPARISON OF ALEXNET, GOOGLENET & SQUEEZENET

Name of the pre-trained network used for transfer learning	Size of the input image	Maximum number of epochs	iterations	training time
SqueezeNet	227*227*3	15	3750	87m7sec
AlexNet	227*227*3	15	3750	109m1sec
GoogleNet	224*224*3	15	3750	71m3sec







Overall classification accuracy and Kappa score for differenttransfer learning models is shown in Table 3

TABLE III. TABLE TYPE STYLES

Name of the pre-trained network used for transfer learning	**Accuracy**	**Kappa Score**
SqueezeNet	99.82%	0.9981
AlexNet	98.92%	0.9873
GoogleNet	97.48%	0.9745

V. CONCLUSION

In this work Alex net, Google Net & SqueezNet are used for classification of faults in a distribution system. AlexNet has shown a classification accuracy of 98.92%. The simulation results show that the test accuracy for SqueezeNet is maximum, i.e., 99.82%, so, it is best choice for fault type classification in the test distribution system. In future, potential of other transfer learning schemes for this problem will be investigated.

REFERENCES

[1] Acácio, L. C, et al. Evaluation of the impact of different neural network structures and data input on fault detection. Proc. IEEE PES Innov. Smart Grid Technol. Conf. Latin Amer. 2017; pp. 1–5.

[2] Bengio, Lecun Y., Hinton, G. Deep learning, Nature. 2015; 521: pp. 436–444.

[3] Aslan, Y., Yağan, Y. E. Artificial neural-network-based fault location for power distribution lines using the frequency spectra of fault data, Electrical Engineering,2017; 99: pp. 301–311.

[4] Chanda, N. K., Fu, Yong. ANN- Based fault classification and location in MVC shipyard power systems, North American Power Symposium. 2011; pp. 1-7.

[5] Tiwari, G., Saini, S. Estimation of Location and Fault Types Detection Using Sequence Current Components in Distribution Cable System Using ANN. Lecture Notes in Networks and Systems. 2022; 339: pp. 119-128. https://doi.org/10.1007/978-981-16-7018-3_9

[6] Chen,W.-H., Liu, C.W., Tsai, M.S. On-Line Fault Diagnosis of Distribution Substations Using Hybrid Cause-Effect Network and Fuzzy Rule-Based Method. 2000; pp. 315-322.

[7] Tiwari, G., Saini, S. Neuro-Fuzzy Access for Detection of Faults in an Underground Cable Distribution System. International Journal of Recent Technology and Engineering. 2019; 8/2S8: pp. 1558–1562. doi: 10.35940/ijrte.b1103.0882s819.

[8] Dehghani, M. M., Khooban, H., Niknam, T. Fast fault detection and classification based on a combination of wavelet singular entropy theory and fuzzy logic in distribution lines in the presence of distributed generations. Int. J. Electr. Power Energy System. 2016; 78: pp. 455–462.

[9] De Souza, J. C. Stacchini. Alarm processing in electrical power systems through a neuro-fuzzy approach, IEEE Transactions on Power Delivery. 2004; 19: pp. 537–544.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8298
***Article Received:** 08 July 2023 **Revised:** 27 August 2023 **Accepted:** 18 September 2023*

[10] He, M., He, D. Deep Learning Based Approach for Bearing Fault Diagnosis. IEEE Transactions on Industry Applications. 2017; 53: pp. 3057–3065.

[11] Hosseini, Z., Mahoor, S. M., Khodaei, A. AMI-Enabled Distribution Network Line Outage Identification via Multi-Label SVM. IEEE Transactions on Smart Grid. 2018; 9: pp. 5470–5472.

[12] Nimr Nimr, A. H. . ., & Naimi, S. . (2023). Improving Performance of Project through Utilizing Statistical Control Chart Based on Adaptive Management and Scientific Engineering. International Journal of Intelligent Systems and Applications in Engineering, 11(4s), 587–593. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2730.

[13] Iandola, F., et al. SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5 MB model size, arXiv: 1602.07360. 2016.

[14] Jamil, M. R., Singh; Sharma, S. K. Fault identification in electrical power distribution system using combined discrete wavelet transform and fuzzy logic. Journal of Electrical Systems and Information Technology. 2015; 2: pp. 257–267.

[15] Jana, S. Dutta, G. Wavelet entropy and neural network based fault detection on a non-radial power system network. IOSR J. Electr. Electron. Engineering. 2012; 2: pp. 26–31.

[16] Jung, H., et al. CNN-based Weighted Ensemble Technique for ImageNet Classification. IEMEK Journal of Embedded Systems and Applications. 2000; 15: pp. 197–204.

[17] Klomjit, J. Ngaopitakkul, A. Selection of proper input pattern in a fuzzy logic algorithm for classifying the fault type in underground distribution system. In Proc. IEEE Region Conf. (TENCON). 2016; pp. 2650–2655.

[18] Wang, N. V., Aravinthan, Ding, Y. Feeder-level fault detection and classification with multiple sensors: A smart grid scenario. Proc. IEEE Workshop Statist. Signal Process. (SSP). 2014; pp. 37–40.

[19] Shafiullah, MD, Abido, M. A. S-Transform based FFNN approach for fault detection and classification distribution grid. IEEE Access. 2008; pp. 8080-8088.

[20] Zhang, J., et al. An ANFIS-based fault classification approach in power distribution system. Int. J. Electr. Power Energy System. 2014; 49: pp. 243–252.

[21] Prof. Parvaneh Basaligheh. (2020). Mining Of Deep Web Interfaces Using Multi Stage Web Crawler. International Journal of New Practices in Management and Engineering, 9(04), 11 - 16. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/94.

[22] Thukaram, D., Khincha, H. P., Vijaynarasimha, H. P. Artificial neural network and support vector machine approach for locating faults in radial distribution systems. IEEE Transactions on Power Delivery. 2005; 20: pp. 710–721.

[23] Zheng, G. Fruit and Vegetables Classification System Using Image Saliency and Convolutional Neural Network. IEEE 3rd. Information Technology and Mechatronics Engineering Conference. 2017; pp. 613–617.

[24] Tamilselvan, P., Wang, P. Failure diagnosis using deep belief learning based health state classification, Reliability Engineering & System. 2013; 115: pp. 124–135.

[25] Alom, M. Z., Taha, T. M., Yakopcic, C., Westberg, S., Sidike, P., Nasrin, M. S., Van Esesn, B. C., Awwal, A. A., & Asari, V. K. The History Began from AlexNet: A Comprehensive Survey on Deep Learning Approaches. arXiv. 2018; pp. 1-38.

[26] Iandola, F. N., Han, S., Moskewicz, M. W., Ashraf, K., Dally, W. J., & Keutzer, K. (2016). SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size. 2016: 1-13.

[27] Piyush Kant, Shahedul Haque Laskar, Jupitara Hazarika, Rupesh Mahamune. CWT Based Transfer Learning for Motor Imagery Classification for Brain Computer Interface. Journal of Neuroscience Methods. 2020; 345: pp.1088-96

[28] Kanna, D. R. K. ., Muda, I. ., & Ramachandran, D. S. . (2022). Handwritten Tamil Word Pre-Processing and Segmentation Based on NLP Using Deep Learning Techniques. Research Journal of Computer Systems and Engineering, 3(1), 35–42. Retrieved from https://technicaljournals.org/RJCSE/index.php/journal/article/view/39.

[29] Pan, S. J., Yang, Q. A survey on transfer learning. IEEE Transactions on Knowledge and Data Engineering. 2010; 22: pp. 1345–1359.

[30] Li, W., Monti, A., Ponci, F. Fault Detection, and Classification in Medium Voltage DC Shipboard Power Systems with Wavelets and Artificial Neural Networks. IEEE Transactions on Instrumentation and Measurement. 2017; 63: pp. 2651-2665.

[31] Ma, Yue, et al. Dc fault detection and pulsed load monitoring using wavelet transform-fed lstm autoencoders. IEEE Journal of Emerging and Selected Topics in Power Electronics. 2020; 9: pp. 7078-7087.

[32] Yulia Sokolova, Deep Learning for Emotion Recognition in Human-Computer Interaction , Machine Learning Applications Conference Proceedings, Vol 3 2023.

[33] Ma, Yue, et al. Pulsed-Power Load Monitoring for an All-Electric Ship: Utilizing the Fourier Transform Data-Driven Deep Learning Approach. IEEE Electrification Magazine. 2021; 9: pp. 25-35.

[34] Senemmar, S., Zhang, J. Deep Learning-based Fault Detection, Classification, and Locating in Shipboard Power Systems. IEEE Electric Ship Technologies Symposium (ESTS). 2012; pp. 1-6.