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Hybrid CNN–SVM Based Fault Classification in Power Distribution Systems Using SqueezeNet and ResNet-18

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ABSTRACT

Reliable operation of electrical distribution systems requires fast and accurate fault diagnosis to ensure grid stability and continuity of supply. This paper presents a hybrid fault classification approach that integrates deep learning and Support Vector Machine (SVM) techniques for effective fault identification in power distribution networks. A Convolutional Neural Network (CNN) is employed to automatically extract discriminative features from three-phase current signals obtained under fault conditions. These signals are generated using PSCAD simulations on an IEEE standard distribution system and converted into image-based representations for analysis. The extracted features are subsequently classified using an SVM to identify and categorize various fault types. Pretrained CNN architectures, namely SqueezeNet and ResNet-18, are utilized to develop hybrid CNN–SVM models within the MATLAB environment. The combination of CNN-based feature extraction and SVM-based classification significantly enhances fault classification performance across diverse operating scenarios. Experimental results demonstrate that the proposed SqueezeNet–SVM hybrid model achieves superior performance, with an accuracy of 99.95%, precision of 99.98%, sensitivity of 99.6%, and specificity of 99.7%. The proposed methodology improves fault classification accuracy, reduces system downtime, and enhances the reliability and resilience of power distribution networks, making it suitable for practical deployment in modern smart grids.

Keywords: Convolutional Neural Network, Distribution System Sensitivity, Fault classification, Specificity, Kappa Score.

INTRODUCTION

Short circuit faults resulting in power loss are a constant threat to distribution systems. As a result, it is critical to accurately identify and correct faults as soon as possible once they arise to complete a rapid restoration. The application of fault diagnosis techniques used in transmission grids to distribution grids is hampered by the structural complexities inherent in distribution grids, including non-homogeneity and an abundance of laterals [1]. Distribution lines are vulnerable to severe weather and environmental circumstances, which include thunderstorms, icing, tree interference, bird nesting, destruction, hurricanes, and aging, as well as human activities and a lack of maintenance and care.

Examples of these conditions include lightning strikes, icing, tree interference, bird nesting, breakage, and aging. Electrical faults are disruptive to the flow of electricity and reduce the effectiveness of power networks. Therefore, one of the primary objectives of the distribution lines is to lessen their effects as much as is humanly possible. A fault classification approach that is extremely dependable, quick, and precise is required [2-4] in order to guarantee that end users will never be without power. This becomes more important as as the level of automation in power distribution systems are growing at a very fast rate. To take these changes into account, artificial intelligent methods need to be used to deal with information from distribution systems [5].

In recent years, there has been a lot of interest in the study of fault classification methods in power transmission systems [6-9]. Due to differences in ways of connecting networks, grounding and protecting relays, etc., these works cannot be used directly in power distribution systems. In a distribution system, several physical factors including voltages of different generators, the phase difference between any two generators, resistance at the time of faults, fault inception angle, the location of the fault, and the length of the distribution lines etc, are measurable but are not always the same. Numerous research have employed fault diagnosis approaches based on machine learning, utilising data from various contexts to address the uncertainties associated with distribution systems [10-15].

The process of deep learning (DL) can autonomously extract significant characteristics from raw signal data, hence eliminating the influence of different artificial learning experiences on the extraction of these features [16,17]. Deep learning (DL) methods have been found to outperform traditional machine learning techniques due to their ability to address the limitations of the latter and get greater results. Convolutional Neural Networks (CNNs) belong to the realm of deep learning algorithms and have demonstrated notable success in the domains of image recognition and classification. In addition to the aforementioned models, namely Alexnet, Googlenet, ResNet, and SqueezeNet, it is worth noting that these convolutional neural network architectures are pre-trained and also they have demonstrated remarkable performance in current years [18]. Taking these research gaps into consideration, we present a comprehensive hybrid deep learning-based system for fault classification in this paper. The utilization of images of time series of fault currents by hybrid CNN-SVM model to discover visual patterns to monitor the state of the circuit is innovative in this work.

The primary contributions of this paper are as follows:

- Development of a hybrid deep learning model for classification of both symmetrical and unsymmetrical faults (total types =11) in a distribution system & comparison of classification accuracy of the proposed model with state-of-the-art models.
- Performance of the proposed model is tested for four pre-trained CNN models & a comparison of their classification accuracy is done.
- The model directly accepts images of 3- phase fault current time series data, thus eliminating the use of any other signal processing or feature extraction technique.
- Model is a high-performance classifier using a combination of techniques; CNN models to pull out deep features and SVM to classify deep features.
- The model is generalized by considering different conditions of occurrence of faults, e.g., different fault resistances, fault inception angles, and fault locations.
- The proposed hybrid model trains the dataset quickly and uses simple computations, while CNN models alone take a long time to train the dataset and also use complicated computations.

THEORETICAL FRAMEWORK

This study involves the modeling and simulating an IEEE 13-node test Radial topology, which is illustrated in Fig. 1. The feeder is equipped with a 4.16 KV voltage source. The PSCAD environment is utilized to generate data to train and test a deep-learning model.

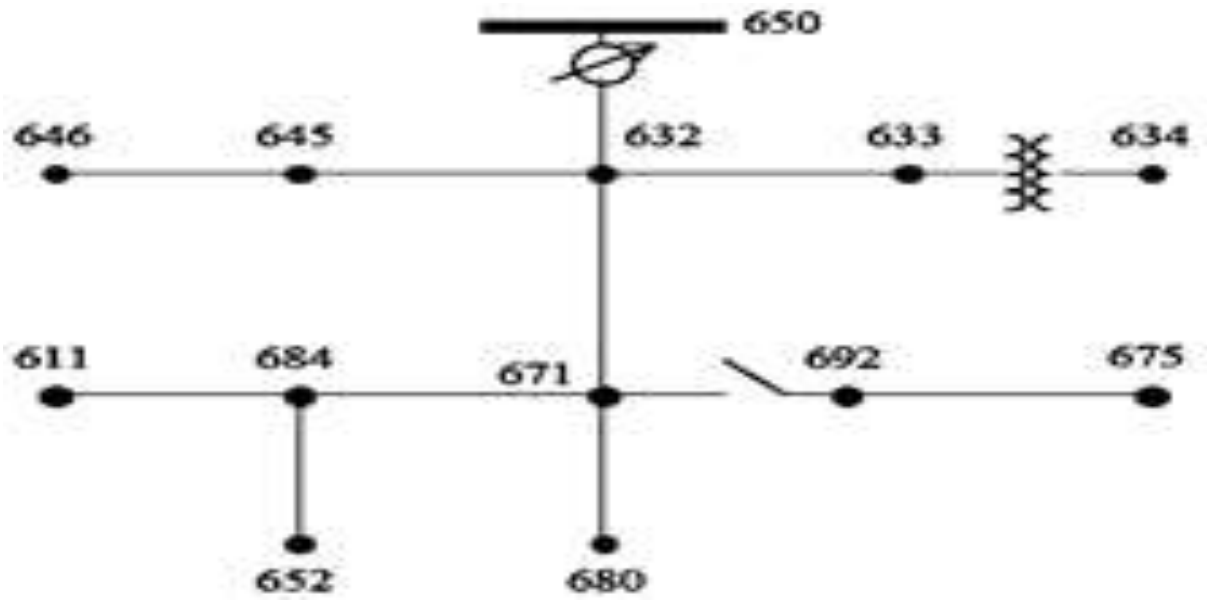


Fig. 1 IEEE 13-Node Test Feeder

Transfer learning is a method for efficiently transferring knowledge from one model to another. The accuracy of a model that will be trained on a smaller dataset can be improved by using this technique, which is frequently used for domain adaptation. Transfer learning is accomplished by using a model that has already been trained. There are a few distinct applications of transfer learning, and each one is dependent on a unique set of circumstances, such as the degree to which a dataset is compatible based on the size of the dataset, the size of the pre-trained model's training dataset, and the amount of computational power. Two distinct CNN models employed in this work are detailed in the following subsections.

2.1. SqueezeNet

The network imposes a constraint on the maximum dimensions of a submitted image, limiting it to 227 pixels on each side. To access additional pretrained networks, users can conveniently browse to the specified place within the MATLAB® software. Smaller deep neural network (DNN) architectures offer many benefits as compared to bigger DNN systems of similar accuracy, mostly in terms of their size. First and foremost, there is a need for decreased bandwidth. Lastly, the installation of smaller DNNs on field-programmable gate arrays (FPGAs) and other hardware with limited memory is straightforward. Despite having 50 times fewer parameters, this model is capable of attaining accuracy levels comparable to AlexNet on the ImageNet dataset. SqueezeNet is composed of 18 convolutional neural layers, as depicted in Fig. 5. After undergoing training, the network can categorize photos into a diverse range of 1000 object categories, encompassing various species. The network exhibits the capacity to acquire intricate feature representations for a diverse range of photographs.

SqueezeNet, a convolutional neural network, is composed of a total of 18 distinct layers. The utilisation of the ImageNet database, which encompasses a vast collection of over one million images, enables the loading of a pre-trained network [20]. The pre-existing neural network can accurately categorise photos of various objects into a comprehensive set of 1,000 distinct groupings, encompassing items such as "keyboard," "mouse," "pencil," as well as a diverse range of animal species. This has facilitated the network in acquiring the ability to generate intricate feature representations for diverse forms of images. The purpose of this function is to generate and provide a SqueezeNet v1.1 network. The SqueezeNet v1.1 networks exhibit a level of accuracy that is similar to that of the SqueezeNet v1.0 networks. However, they achieve this accuracy while demanding a reduced number of floating-point operations per prediction, as shown in reference [21].

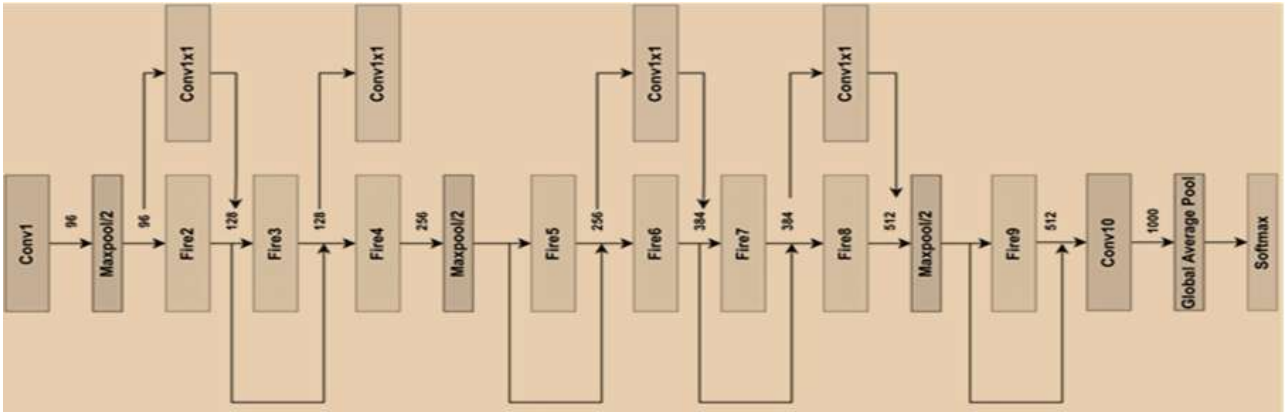
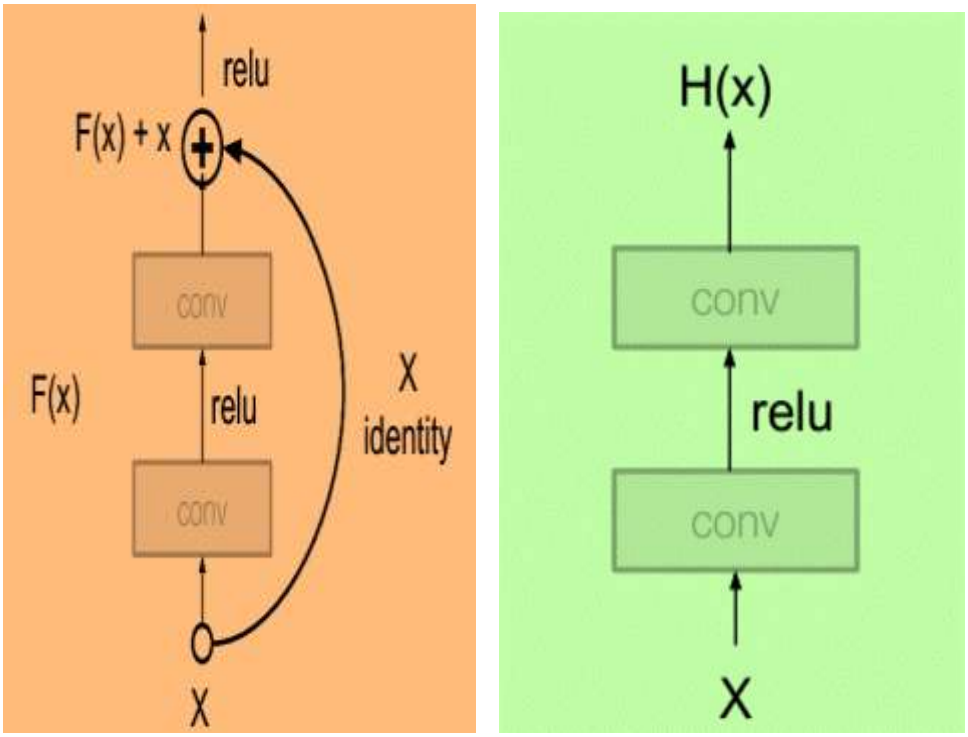


Fig. 2 Squeeze Net layer Architecture

2.2 ResNet-18

Within the ResNet (Residual Networks) model family, ResNet-18 is a convolutional neural network design. In their 2015 study titled "Deep Residual Learning for Image Recognition," Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun presented it. One of the smallest ResNet architecture versions, ResNet-18 is frequently utilised for image classification applications. The concept of residual blocks, which have shortcut connections (skip connections) that facilitate easier gradient flow during training, is introduced by ResNet-18. Very deep neural networks can be trained thanks to these shortcut connections, which also help to avoid the vanishing gradient problem. Because ResNet-18 strikes a reasonable balance between model size and performance, it has gained popularity for a variety of computer vision tasks, such as object identification, picture segmentation, and image classification. It is more computationally efficient and appropriate for applications with limited resources because it is shallower and smaller than larger ResNet variations like ResNet-50 or ResNet-101.[22]. This lets it do better at picture recognition tasks. ResNet-18 is trained using a method called "backpropagation." This method involves finding the gradients of the loss function with respect to the weights and biases of the network and changing them using an optimization algorithm like "stochastic gradient descent." It has been used for a number of computer vision tasks, such as classifying images, finding objects, and separating them. It incorporates residual mapping ($H(x) = F(x) + x$) into its network instead of desired underlying mapping ($H(x)$). Resnet50 refers to a variation that can work with 50 neural network layers. Figures 3a & 6b show a plain layer, and residual block for ResNet-18 architecture respectively. The ResNet-18 architecture is made up of 3_3 convolutional layers stacked on top of each other. ResNet-18 has the ability to train deeper networks without compromising performance and is easier to optimize.



(a) (b)

Fig. 3. (a) Plain layer (b) Residual block

2.3. Support Vector Machine

The Support Vector Machine is a well-known supervised machine learning algorithm that can be used for classification and regression analysis. It is a non-parametric and discriminative learning method aimed at determining the optimal boundary (or hyperplane) that splits data points into different groups. Figure 4 shows that the objective of this strategy is to find the best boundary (or hyperplane). In a binary classification task, an SVM algorithm's purpose is to find the hyperplane with the greatest possible difference in margin between two classes of data points. The support vector machine (SVM) selects the hyperplane that improves the margin, resulting in greater model generalization to previously unseen data. SVMs can also cope with data that is not linearly separable by translating it to a higher-dimensional feature space, where it may become linearly separable. This is accomplished by employing a technique known as the kernel trick, which avoids the need for an explicit computation for the highly dimensional feature space. SVMs have found widespread application in a wide range of application disciplines, including text classification, image classification, and bioinformatics, amongst others. They have also been designed to deal with problems involving several categories of categorization and regression analysis.[23].

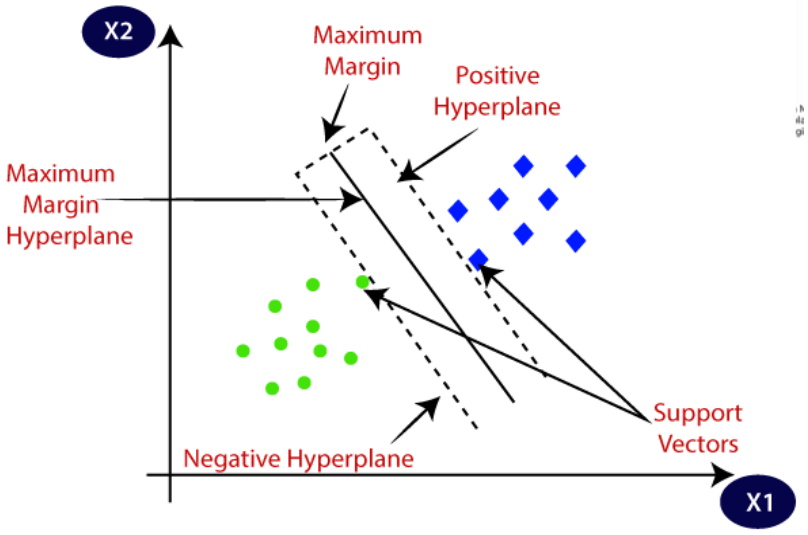


Fig. 4 Support Vector Machine

METHODS

The diagram in Figure 5 illustrates the entire sequence of tasks. The process entails the acquisition of fault current time series data through the utilisation of simulation software known as PSCAD. Subsequently, the data is exported to MATLAB, so generating images that can be utilised as input data for convolutional neural networks (CNN).

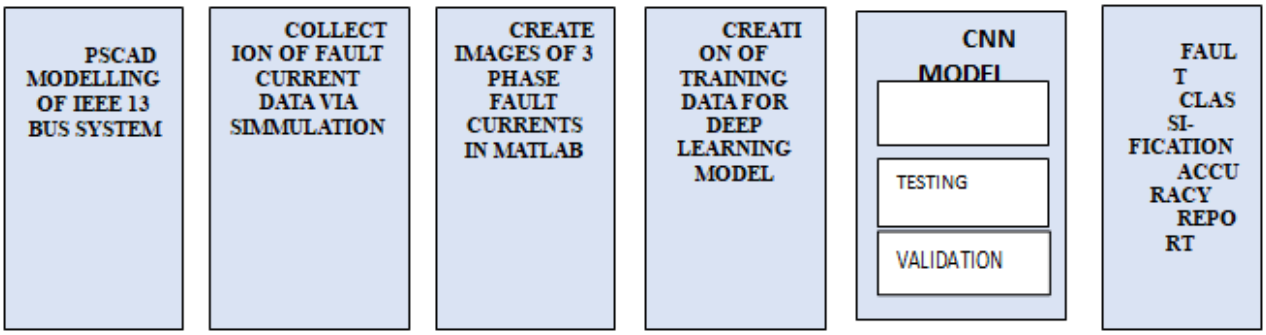


Fig. 5. Methodology

The training dataset for Convolutional Neural Networks (CNNs) comprises labeled data that correspond to different fault kinds. The CNN/HYBRID-CNN model is utilised to train and evaluate fault classification accuracy by employing the given input-output data.

3.1. Fault current measurements and Creating Training/Testing Data

Within any power distribution systems, there are five discernible types of fault, specifically: L to G fault, L to L fault, L to L to G fault, L to L to L fault, and L to L to L to G fault. The aforementioned fault categories include a comprehensive set of 11 distinct failure circumstances, taking into account the analysis of three lines. This study entails the measurement and documentation of three-phase electrical currents in various failure conditions across distinct scenarios, as outlined in Table 1. A simulation model is established within the PSCAD/EMTDC framework to fulfil this objective. The duration of the simulation run for this model is 1.3 seconds, with the failure event occurring within the time interval of 0.2 to 1 seconds. Consequently, a cumulative count of 5568 cases is observed, comprising 5120 cases (8 nodes * 8 resistances * 8 inception angles) for each of the 10 types of faults, and an additional 448 cases (8 nodes * 7 resistances * 8 inception angles) specifically for the ABC fault. These cases involve the measurement of time series data for 3-phase current signal during each fault. The collected samples then organized into vector with 5568 rows, which serves as training/testing/validation datasets for the Convolutional Neural Network (CNN). MATLAB imports a set of fault instances for training. The output training data is composed of a label that represents the type of fault in the input data.

Table 1. Different Conditions for Fault Creation

Parameter	Values
Faulty Nodes	632,633,634,650 671,675,680,692 nodes
Different Inception angles	10*,35*,60*,85*,110*,135*, and 185* degree
Resistances Value	0,0.5,50,100,500,1000,1500 ohm

3.2 Hybrid CNN-SVM Model

This section provides a comprehensive discussion on the hybrid deep learning model employed in this study. The process consists of two main components. In the initial phase, deep learning models such as ResNet, and SqueezeNet are employed to extract deep feature maps. These maps are then converted into feature vectors and subsequently sent to the second phase, as depicted in Figure 6. In the subsequent phase, the Support Vector Machine (SVM) model is responsible for partitioning the feature maps obtained in the preceding stage into distinct clusters, with the objective of facilitating the classification process. One rationale for employing these hybrid technologies is in their ability to operate effectively with computer specifications of moderate cost, in contrast to CNN models that necessitate high-priced computer specifications. In addition, hybrid methodologies exhibit expedited training of datasets and employ elementary calculations, whereas CNN models necessitate prolonged training periods for datasets and include intricate computations.

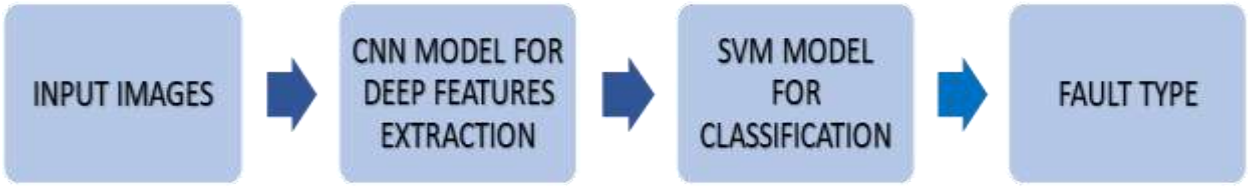


Fig. 6. Hybrid CNN-SVM Model

3.3 Performance Evaluation Metrics

In this work, testing data is used to evaluate the effectiveness of each strategy. The performance of the proposed model is evaluated in terms of five performance measures as described Table 2. Here, 'N' represents the total classes.

Table. 2 Expression for Performance Parameters

Sr. No.	Name of Performance Parameters	Expressions
1	Classification Accuracy	Accuracy = $(\frac{Ncorrect}{Ntotal})$*100%
2	Kappa Score	K = $\frac{Acc-Racc}{1-Racc}$, Where Racc = 1/N
3	. Precision	Precision = $\frac{TP}{TP+FP}$100
4	Sensitivity	Sensitivity =$\frac{TP}{TP+FN}$*100
5	Sensitivity	specificity = $\frac{TN}{TN+FP}$*100

SIMULATION RESULTS WITH DISCUSSION

Here in this research paper introduces a PSCAD Simulink model of the IEEE 13 node Radial distribution topology. The model is designed to simulate 11 diverse types of faults that can occur at eight specific nodes. The simulation platform possesses the capacity to accurately reproduce diverse fault categories, including a broad spectrum of faulty resistance values and faulty inception angle values. The dataset utilized for training a Convolutional Neural Network (CNN) comprises visual representations illustrating a sequential progression of three-phase fault currents. The images shown in this study were generated utilizing the MATLAB software version 2021a.

4.1 Splitting input dataset for training and testing

In the current iteration of the manuscript, a splitting strategy is employed where 75% of the available data is allocated for training purposes, while the remaining 25% is reserved for testing and validation. There was a total of 5568 incidents observed across 11 distinct fault categories. There are a total of 5120 cases, each consisting of 10 types of faults. These instances are determined by the combination of 10*8 resistance values, 8 nodes, and 8 inception angles. The remaining 448 cases are specifically connected to the ABC fault, determined by 7 resistance values, 8 nodes, and 8 inception angles. The comprehensive dataset comprises fault category labels and a compilation of 5568 images illustrating data of three-phase fault currents.

At the outset, a collection of training data comprising 3898 photographs, a validation dataset consisting of 1115 images, and a test and prediction dataset encompassing 555 images are generated. Following this, a series of pre-processing operations are carried out, including scaling, rotation, and reflection. Image scaling is carried out to ensure that the input scale of the deep learning network remains consistent. To address the potential issue of overfitting in the network, random pre-processing techniques are utilised to enrich the visual input. The convolutional neural network (CNN) models utilised in this research encompass ResNet-18, and SqueezeNet. Table 3 displays the training parameters of CNN models.

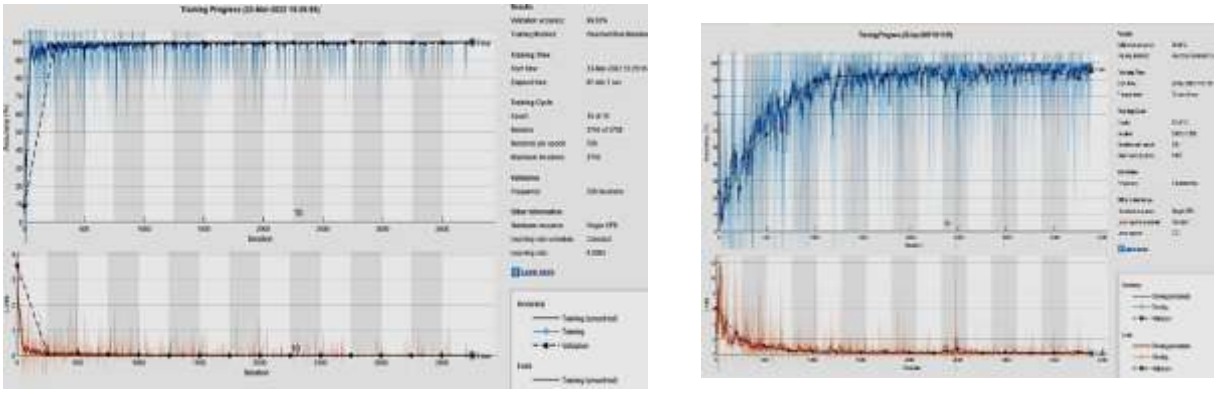
Table 3. Training parameters

Name of the CNN architecture/ Parameters	SqueezeNet	ResNet-18
Size of image	227*227*3	224*224*3
Min. Batch size	23	23
Max epoch	5780	5780
Initial learning Rate	0.0003	0.0003
Validation Frequency	250	250
Training Time	87m7sec	65m31sec
Execution Environment	CPU	CPU

4.2 Training of Deep Learning Model

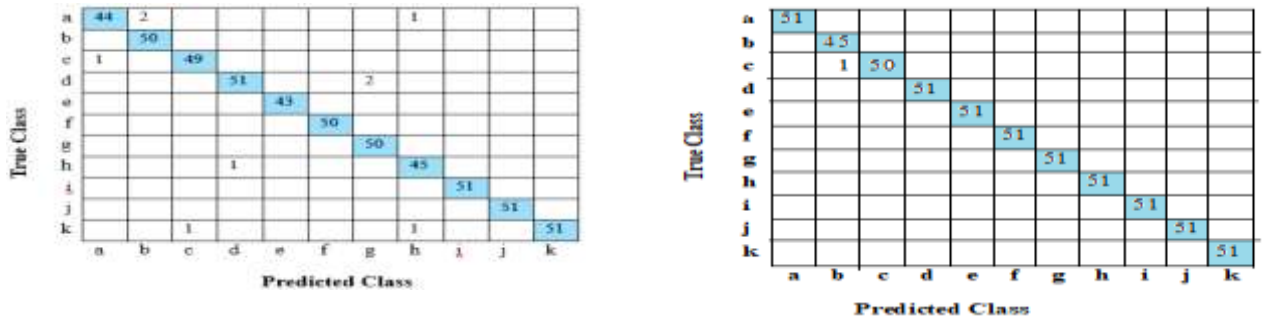
Four types of pretrained CNN models are trained for fault classification purposes; the training curve for each is represented in Figs. 7 (a-b) respectively.

The Confusion Matrices for the test data are depicted in Figures 8(a-b), correspondingly for the Squeeze Net and ResNet-18 models. In the context of confusion matrices, the classes denoted as a to k correspond to specific types of short circuit faults. These faults are categorized as follows: A to B, A to B to C, A to B to C to G, A to B to G, A to G, B to C, B to C to G, B to G, C to A, C to A to G, and C to G. The table presented in Table 4 displays the classification accuracy, precision, sensitivity, specificity, area under the curve (AUC), and Kappa score for several transfer learning models.



(a) **(b)**

Fig 7. Training Progress: a) Squeeze Net b) ResNet-18



(a) **(b)**

Fig. 8 CM (Confusion Matrices): a) Squeeze Net b) ResNet-18

Table 4. Comparison of performance of ResNet & SqueezeNet

Name of the Model	Squeeze Net with SVM	AlexNet With SVM	Google Net With SVM	ResNet-18 with SVM
Accuracy%	99.95%	99.60%	98.9%	99.30
Kappa Score	0.998	0.995	0.987	0.99
Precision%	99.98	97.2	99.0	98.9
Sensitivity%	99.6	97.1	98.9	99.2
Specificity%	99.7	97.15	98.75	99.25

4.3 Performance of CNN-SVM Hybrid Model

In this model features extracted from CNN model are given as input to SVM for classification. Pre-trained CNN model SqueezeNet, is found to have best classification results when used with SVM classifier as shown in Table 5.

Table 5 Performance Results for Hybrid CNN-SVM Models

Reference no.	Year	Technique	Overall Accuracy (%) (Without noise)
Proposed Technique	**2025**	**SqueezeNet+SVM**	**99.95%**
[24]	2022	Robust Semi-Supervised Prototypical Network (RSSPN)	91.10%
[25]	2021	KNN- Bayesian Method	97%
[26]	2021	Wavelet packet transform & support vector machine	98.8%
[27]	2020	CNN-LSTM	89%
[28]	2020	Deep CNN	99.3%

Comparison of Results

This section includes a comparison of the accuracy of the suggested technique to those of other procedures used in the literature. As shown in Table 6. It is self-evident that the proposed strategy is capable of diagnosing the faults in a distribution grid with maximum accuracy and is better than the other techniques presented in the literature. Additionally, this method has shown positive results regardless of the fault resistance magnitude or fault inception angle. measure and location of faulty node.

Table 6. Comparison of Accuracy with Literature

Name of the Model	SqueezeNet	ResNet
Accuracy	99.82%	96.24
Kappa Score	0.9981	0.961
Precision	99.85	97.05
Sensitivity	99.83	97.01
Specificity	99.84	97.03

CONCLUSIONS

Compared with conventional methods, the hybrid deep learning–support vector machine (DL–SVM) approach significantly improves fault classification accuracy, which is crucial for the reliable operation of power distribution systems. Convolutional neural networks (CNNs) effectively extract discriminative features directly from raw signals, reducing reliance on manual feature engineering and enhancing adaptability to diverse fault conditions. The hybrid model also demonstrates strong generalization capability, enabling accurate identification of previously unseen faults under changing system conditions, which is essential for practical deployment. In this study, AlexNet, GoogleNet, ResNet-18, and SqueezeNet were evaluated for fault classification in an IEEE 13-bus radial distribution system. Integrating CNNs with SVM further enhanced performance, with AlexNet–SVM achieving an accuracy of 99.10%, while SqueezeNet–SVM attained the highest accuracy of 99.95%, making it the most effective model for fault

classification. Overall, the proposed hybrid DL–SVM framework reduces false alarms while improving accuracy, adaptability, and system reliability. Future work may focus on real-time implementation, advanced sensor integration, and exploration of alternative hybrid deep learning and machine learning models.

REFERENCES

1. Acácio, L. C, et al. Evaluate 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, doi:10.1109/ACCESS.2018.2809045.
2. J. Hare et al., Fault diagnostics in smart micro-grids: A survey, Renewable & Sustainable Energy Reviews 60 2016; pp. 1114–1124.
3. M. Bjelić, B. Brković, M. Žarković, T. Miljković, Fault detection in a power transformer based on reverberation time, International Journal of Electrical Power & Energy Systems. 2022; pp. 107825.
4. M. Khoshbouy, A. Yazdaninejadi, T. G. Bolandi, Transmission line adaptive protection scheme: A new fault detection approach based on pilot superimposed impedance, International Journal of Electrical Power & Energy Systems. 2022; pp.107826.
5. J. Zheng, P. Li, K. Xu, X. Kong, C. Wang, J. Lin, C. Zhang, A distance protection scheme for HVDC transmission lines based on the steady-state parameter model, International Journal of Electrical Power & Energy Systems. 2022; pp.107658.
6. D. Guillen, M. R. A. Paternina, A. Zamora, J. M. Ramirez, and G. Idarraga, "Detection and classification of faults in transmission lines using the maximum wavelet singular value and Euclidean norm," IET Gener., Transmiss. Distrib., vol. 9, no. 15, Nov. 2015; pp. 2294–2302.
7. M. Jamil, S. K. Sharma, and R. Singh, "Fault detection and classification in an electrical power transmission system using artificial neural network," SpringerPlus, vol. 4, no. 1, pp. 334, 2015.
8. A. Prasad and J. B. Edward, "Application of wavelet technique for fault classification in transmission systems," Procedia Comput. Sci., vol. 92, 2016; pp. 78–83.
9. P. Rajaraman, N. A. Sundaravaradan, R. Meyur, M. J. B. Reddy, and D. K. Mohanta, "Fault classification in transmission lines using wavelet multiresolution analysis," IEEE Potentials, vol. 35, no. 1, Jan./Feb. 2016; pp. 38–44.
10. P. Ray and D. P. Mishra, "Support vector machine based fault classification and location of a long transmission line," Eng. Sci. Technol., Int. J., vol. 19, no. 3, 2016; pp. 1368–1380.
11. A. M. El-Zonkoly and H. Desouki, "Wavelet entropy-based algorithm for fault detection and classification in FACTS compensated transmission line," Int. J. Elect. Power Energy Syst., vol. 33, no. 8, 2011; pp. 1368–1374.
12. J. Zhang, Z. Y. He, S. Lin, Y. B. Zhang, and Q. Q. Qian, "An ANFIS-based fault classification approach in power distribution system," Int. J. Electr. Power Energy Syst., vol. 49, Jul. 2013pp. 243–252.
13. Bengio, Lecun Y., Hinton, G. Deep learning, Nature. 2015; 521: pp. 436–444. doi:10.1038/nature14539
14. 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, doi: 10.1007/s00202-016-0428-8
15. Chanda, N. K., Fu, Yong. ANN- Based fault classification and location in MVDC shipboard power systems, North American Power Symposium. 2011; pp. 1-7, doi:10.1109/NAPS.2011.6025172
16. 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
17. 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, doi: 10.1109/61.853009
18. 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.
19. 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, https://doi.org/10.1016/j.ijepes.2015.11.048
20. 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, DOI: 10.1109/TPWRD.2003.823205.
21. He, M., He, D. Deep Learning Based Approach for Bearing Fault Diagnosis. IEEE Transactions on Industry Applications. 2017; 53: pp. 3057–3065, doi: 10.1109/TIA.2017.2661250.
22. 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, DOI: 10.1109/TSG.2018.2849845
23. Iandola, F., et al. SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5 MB model size, arXiv: 1602.07360. 2016.
24. T. Zheng et al., "RSSPN:Robust Semi-Supervised Prototypical Network for Fault Root Cause Classification in Power Distribution Systems," IEEE Transactions on Power Delivery, vol. 37, no. 4, pp. 3282–3290, Aug. 2022, doi: 10.1109/TPWRD.2021.3125704.

25. Y. Liang, K. J. Li, Z. Ma, and W. J. Lee, “Multilabel Classification Model for Type Recognition of Single-Phase-to-Ground Fault Based on KNN-Bayesian Method,” IEEE Trans Ind Appl, vol. 57, no. 2, pp. 1294–1302, Mar. 2021, doi: 10.1109/TIA.2021.3049766.
26. 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, DOI: 10.1109/TIM.2014.2313035
27. 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, DOI: 10.1109/JESTPE.2020.3019382.
28. 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, DOI: 10.1109/MELE.2020.3047164.