



Elektrik İletim Hatlarında Arıza Tespiti: Topluluk Makine Öğrenmesi ve Evrişimsel Sinir Ağı Yöntemlerinin Karşılaştırmalı Analizi

Emrah ASLAN^{1*} , Yıldırım ÖZÜPAK² 

¹Bilgisayar Mühendisliği Bölümü, Mühendislik Mimarlık Fakültesi, Mardin Artuklu Üniversite, Mardin, Türkiye.

²Elektrik ve Enerji Bölümü, Silvan Meslek Yüksekokulu, Dicle Üniversite, Diyarbakır, Türkiye.

¹emrahaslan@artuklu.edu.tr, ²yildirim.ozupak@dicle.edu.tr

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Öz

Elektrik güç sistemlerinde artan yük talebini karşılamak amacıyla iletim hatlarının sayısı artarken, buna paralel olarak arıza sayıları da çoğalmaktadır. Dış çevresel etkenlerden kaynaklanan arızalar bu hatlar için ciddi tehdit oluşturabilir ve sistemin zarar görmesine neden olabilir. Bu nedenle, iletim hatlarında oluşan arızaların hızlı ve doğru bir şekilde tespit edilmesi hayati önem taşır. Bu çalışmada, iletim hatlarındaki arızaları belirlemek amacıyla yapay sinir ağı tabanlı bir model geliştirilmiştir. Öncelikle, arıza tespiti için Bagging, AdaBoost ve Gradient Boosting Sınıflandırıcı gibi çeşitli makine öğrenme algoritmaları kullanılmış ve tüm modeller eğitim ve test süreçlerinden geçirilmiştir. Test sonuçlarına göre, Gradient Boosting Sınıflandırıcı algoritması en yüksek başarıyı göstermiştir. Ancak, daha yüksek doğruluğa ulaşmak amacıyla, çalışma kapsamında derin öğrenme tabanlı bir model olan Evrişimsel Sinir Ağı önerilmiştir. Önerilen model ile %99,73 doğruluk oranı elde edilerek makine öğrenme algoritmalarından daha iyi bir başarı sağlanmıştır. Bu sonuçlar, yapay sinir ağı tabanlı modelin iletim hattı arızalarını etkili bir şekilde tespit ederek güç sistemlerinin güvenilirliğini ve sürekliliğini sağlamada önemli bir rol oynadığını göstermektedir.

Anahtar kelimeler: Derin öğrenme, Arıza tespiti, İletim hattı, Makine öğrenmesi, Güç sistemleri

*Yazılan yazar

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Şikayet: fujece@firat.edu.tr

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Fault Detection in Electricity Transmission Lines: A Comparative Analysis of Ensemble Machine Learning and Convolutional Neural Network Methods

Emrah ASLAN^{1*} , Yıldırım OZUPAK² 

¹Department of Computer Engineering, Faculty of Engineering and Architecture, Mardin Artuklu University, Mardin, Türkiye.

²Department of Electricity and Energy, Silvan Vocational School, Dicle University, Diyarbakır, Türkiye.

¹emrahaslan@artuklu.edu.tr, ²yildirim.ozupak@dicle.edu.tr

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Abstract

As the number of transmission lines increases to meet the increasing load demand in electric power systems, the number of faults increases in parallel. Faults caused by external environmental factors can pose a serious threat to these lines and cause damage to the system. Therefore, fast and accurate detection of faults in transmission lines is of vital importance. In this study, an artificial neural network-based model is developed to detect faults in transmission lines. Firstly, various machine learning algorithms such as Bagging, AdaBoost and Gradient Boosting Classifier are used for fault detection and all models are put through training and testing processes. According to the test results, the Gradient Boosting Classifier algorithm showed the highest success. However, in order to achieve higher accuracy, a Convolutional Neural Network (CNN), a deep learning-based model, was proposed in this study. The proposed model achieved an accuracy rate of 99.73%, which is better than that of the machine learning algorithms. These results demonstrate that the neural network-based model plays an important role in ensuring the reliability and continuity of power systems by effectively detecting transmission line faults.

Keywords: Deep learning, Fault detection, Transmission line, Machine learning, Power systems

*Corresponding author

1. Introduction

Electric power systems are continuously expanding to meet the increasing demand for electricity, which increases the complexity of the system and increases the failure rates. Transmission line failures in power systems pose serious threats to the continuous and reliable operation of the system [1]. Factors such as various environmental conditions, weather, equipment aging and unexpected events lead to transmission line failures. This leads to interruption of energy flow and damage to system components. Therefore, fast and accurate detection of transmission line faults is very important for both energy security and reducing economic losses. In this context, the development of reliable and effective solution methods for the detection of transmission line faults has become critical for the energy sector.

Transmission line faults are generally analyzed in two main groups as series and shunt faults. Shunt faults are divided into symmetrical and asymmetrical faults. Single line-to-ground (A-G, B-G, C-G), line-to-line (AB, BC, CA), and double line-to-ground (AB-G, BC-G, CA-G) are examples of asymmetrical faults, whereas triple line faults (ABC) and triple line-to-ground faults (ABC-G) are examples of symmetrical faults. In power systems, the detection and classification of these different types of faults are important for maintaining the stability of the system [2]. Conventional methods are inadequate in the face of increasing system complexity and are ineffective when fast and highly accurate fault detection is required.

Accordingly, in recent years, Machine Learning (ML) and Deep Learning (DL)-based methods have played an important role in fault detection and classification processes. Although DL is a subcategory of ML methods, it is treated as a separate heading in this study due to its widespread use in the literature; this distinction is explicitly made to maintain conceptual integrity. Among ML methods, algorithms such as Bagging Classifier, AdaBoost and Gradient Boosting have attracted attention due to their high accuracy rates, fast processing capacities and their ability to work effectively with large data sets [3]. However, deep learning methods with more layers are becoming increasingly important in processing large and complex data such as electric power systems. Among deep learning models, especially Convolutional Neural Network (CNN) offers a suitable solution for the detection and classification of transmission line faults due to its superior performance in big data and image analysis [4].

In this study, the “Electrical Fault Detection and Classification” dataset available on the Kaggle platform is used for fast, reliable and accurate detection of transmission line faults in electric power systems [5]. This dataset is an important source of information for training fault detection models by providing a large sample detailing various fault types and conditions that occur in the system. The main motivation of the study is to develop an efficient model for classifying different types of faults in transmission lines with high accuracy and minimizing interruptions in power flow. As the complexity of electric power systems increases, fault detection with traditional methods becomes more difficult and the margin of error in the process increases. In this context, it is aimed to classify and detect faults by utilizing the versatile information provided by the data set, especially by using the power of deep learning-based models such as CNN. Thus, it is aimed to maintain uninterrupted energy flow and minimize economic losses.

One of the limitations of this study is that the dataset used may not fully reflect all fault conditions in real-world scenarios. It should be noted that fault detection models may be affected by various environmental factors, line aging, or structural differences in equipment within large-scale electrical systems. In addition, the fact that the dataset used is limited to a certain number of fault types and data obtained under limited conditions may affect the overall performance of the model and its generalizability to other systems. This suggests the need for future training with larger, real-time and dynamic data sets. This study provides a foundation for improving model accuracy and reliability and motivates further studies with more comprehensive datasets and conditions. This research demonstrates the applicability of machine learning and deep learning-based models to improve the reliability of electric power systems and ensure uninterrupted energy flow. The aim of the study is to increase the efficiency of power systems and reduce potential failure costs by quickly and accurately detecting faults in transmission lines. Accordingly, the proposed CNN-based model is expected to make a significant contribution to fault detection and classification in the energy sector. In Section 1 of this study, general information about the problem is given. The following sections of the study are as follows. Section 2 contains the work done for fault detection in transmission lines. Section 3 presents

the materials and methods required for the applications; Section 4 presents the results and discussion. Section 5 presents the conclusions and future work.

2. Literature Review

Fahim et al. proposed an unsupervised capsule network model for the detection and classification of transmission line faults. The model improves performance by learning fault characteristics without using large data sets. It converts three-phase signals into a single image and works with this image. The model has been tested in four different TL topologies and various fault scenarios, providing high reliability and adaptability [6]. Vaish et al. investigated ML methods for power system fault detection. They discussed supervised and unsupervised learning techniques, addressing the challenges of traditional methods. They also emphasized the potential of new methods such as reinforcement learning and transfer learning [7]. Fahim et al. propose a noise-tolerant, accurate fault detection model for microgrid faults. The model performs error minimization using a restricted Boltzmann machine (RBM) and its robustness is verified by testing it with signal variations. The results show that the model provides highly accurate fault detection and is superior to other methods [8]. Shakiba et al. propose a more reliable fault detection system for high-voltage transmission lines than conventional methods. Using CNN, this system performs robustly under various variables and noises, providing accurate detection and localization before the fault occurs [9]. Goni et al. propose a machine learning based system for Fault Detection (FD) and Fault Classification (FC) in transmission lines. FD and FC models are developed with the Extreme Learning Machine (ELM) algorithm for two different transmission lines simulated using MATLAB Simulink. Fault detection with 99.53% and 99.60% accuracy and fault classification with 99.18% and 99.09% accuracy are achieved for TL-1 and TL-2, respectively. The ELM model offered shorter processing time and lower computational complexity compared to traditional neural networks [10]. Kanwal and Jiriwibhakorn investigated artificial intelligence-based methods for fault detection, classification and localization in transmission lines. In the study, fault location with an error of 5.32 km was achieved using an Adaptive Neural-Fuzzy Inference System (ANFIS)-based fault detection and classification approach on the IEEE-9 bus system. The results demonstrate the effectiveness and potential of artificial intelligence techniques in this field [11]. Uddin et al. presented hybrid intelligent protection and control algorithms to improve the performance of distance relays in wind farms. A Decision Tree (DT) fault classifier and Support Vector Machine (SVM) were used for fault localization, and a PI-based control scheme was developed for DFIG-based wind power systems. These methods enhance the reliability and stability of wind farms [12]. Xi et al. developed an SA-MobileNetV3-based method for fault classification in transmission systems. The method employs deep learning by converting three-phase signals into two-dimensional images using CWT and classifies fault features more accurately with the SA module. Tested on a 735 kV transmission line model, the method demonstrates high accuracy and strong generalization capability [13].

Sahu et al. propose a Histogram-Based Gradient Boost (HGB) algorithm for fault detection and localization. The features of fault signals are extracted using spectral-kurtosis and the method is tested on IEEE-33 bus distribution system. HGB is compared with other machine learning methods and its superiority is proved [14]. Hassain et al. developed an Artificial Neural Network (ANN) model for fault detection in power systems with 99% accuracy. The model was tested with data from 14 bus systems and achieved high accuracy, precision and F1 score [15]. Shukla and Deepa used deep learning techniques to classify transmission line faults. In particular, they used ANN and Long-Short-Term Memory (LSTM) to automatically classify fault types (line-to-line, line-to-ground, etc.) and simplify the signal processing [16]. Livani presents a supervised learning method for fault location in complex power transmission lines using high-resolution voltage and current data from smart grids. The method is developed for three-terminal transmission lines and hybrid transmission lines and fault detection is realized using SVM and wavelet transform [17]. Salehimehr et al. developed fast fault detection and localization methods for DC microgrids. The proposed approach combines Compressed Sensing (CS) and Regression Tree (RT) techniques while achieving accurate fault localization using an LSTM model. Simulation results indicate that the method can detect and locate faults within 1 ms with 93% accuracy [18]. Zhu et al. employed a deep learning approach with a weighted loss function to automatically extract power lines from point clouds obtained using UAV-based laser scanners. The method achieved effective results on large-scale data [19]. Li et al. propose a Transformer-based method for short-term voltage stability assessment. The model generates artificial data

using CWGAN-GP to stabilize unstable data sets. In tests on IEEE 39-bus system, the proposed method exhibits strong performance in class imbalance and noisy environments. The results show that the StaaT model is more effective than other methods [20]. Dutta et al. emphasize the importance of ML in power systems. ML algorithms are used in areas such as load forecasting, fault detection, and energy management. In this study, methods such as Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), Recurrent Neural Networks (RNNs), and Decision Trees (DTs) are described, and a case study on fault detection in the IEEE five-bus system is presented [21].

3. Material and Method

In this study, the “Electrical Fault Detection and Classification” dataset published on the Kaggle platform is used to detect and classify electrical transmission line faults. The study aims to accurately classify faults with a deep learning-based CNN model. First, the data in the dataset is analyzed, then appropriate features are selected and prepared for data preprocessing and model training. In addition to the CNN model, machine learning models such as Bagging Classifier, AdaBoost, and Gradient Boosting were also tested, and a comparative performance evaluation was conducted. The flowchart of the study is presented in Figure 1. In the subsequent stages of the research, the model’s performance is evaluated, and its potential benefits for the energy sector are analyzed.

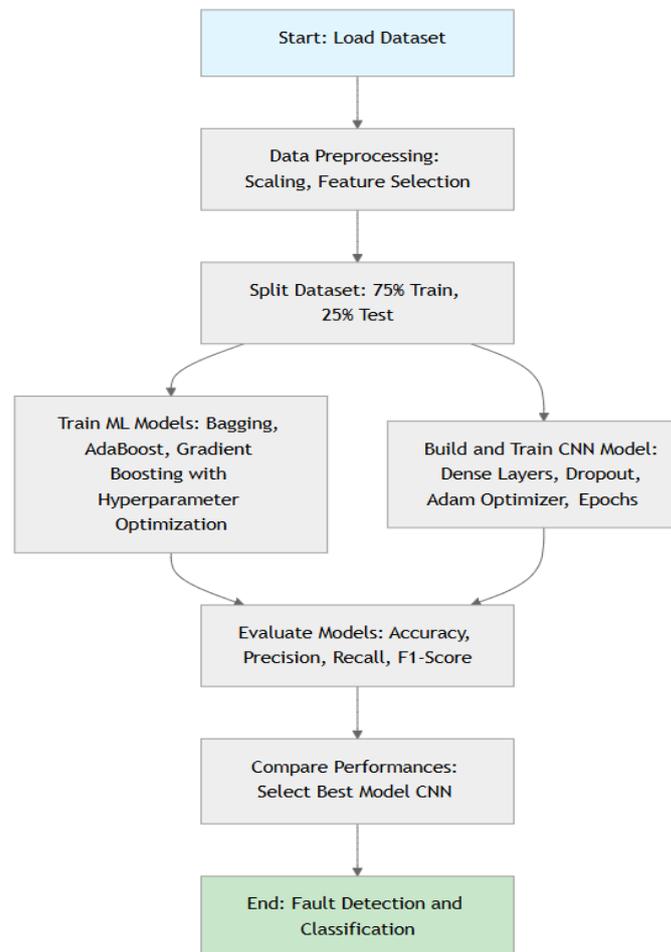


Figure 1. Flowchart of the proposed methodology

3.1. Transmission line model and faults

Fault detection in electricity transmission lines is usually classified according to the types of faults. Faults are divided into two main groups: symmetrical and asymmetrical. Symmetrical faults include triple line faults

(ABC) and triple line-to-ground faults (ABC-G), while asymmetrical faults are more diverse and include single line-to-ground (A-G, B-G, C-G), line-to-line (AB, BC, CA) and double line-to-ground (AB-G, BC-G, CA-G) faults. This classification helps to accurately identify the types of faults in transmission lines. Figure 2 shows the classification of fault types in transmission lines.

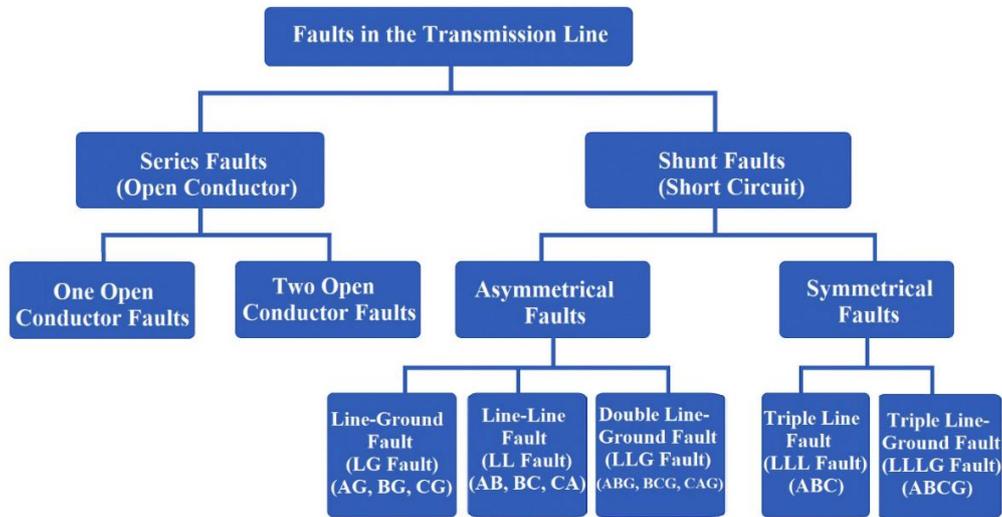


Figure 2. Classification of fault types in transmission line

Figure 3 illustrates the overall methodology for fault detection and classification in transmission lines as a flowchart. It starts with loading the Kaggle dataset, followed by data preprocessing (scaling and feature selection for $I_a, I_b, I_c, V_a, V_b, V_c$) and splitting into 75% training and 25% testing sets. Parallel paths show training of machine learning models (Bagging, AdaBoost, Gradient Boosting) with hyperparameter optimization and the proposed CNN model.

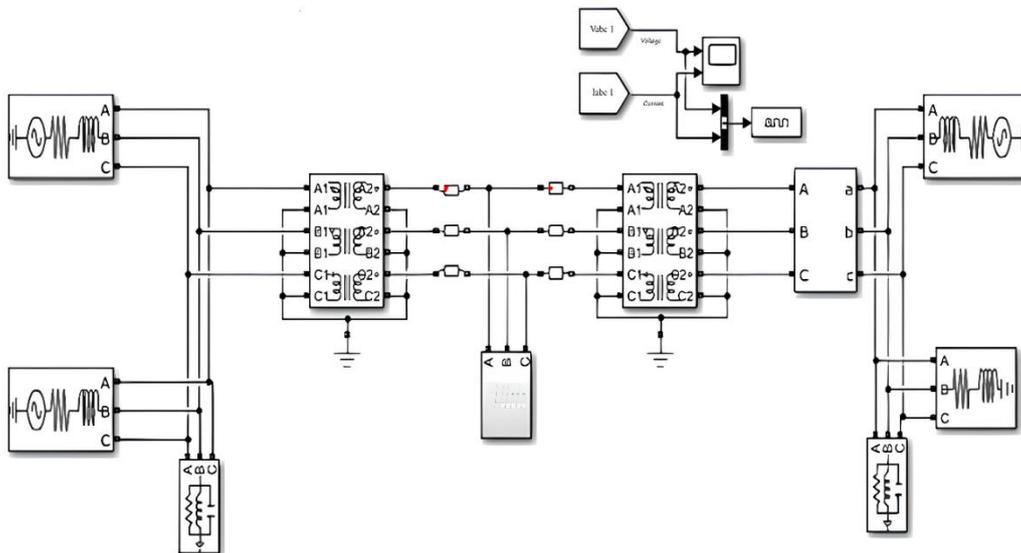


Figure 3. Transmission line model

The power system we examined, shown in Figure 3, consists of a 154kV, 50Hz three-phase transmission line connected to a power supply at both ends. The Artificial Neural Network (ANN) relay used is based on distance relay protection. The model represents a transmission line in Türkiye.

The transmission system is modeled using MATLAB software and various fault types are simulated to generate a fault data set for network training and testing. The power system parameters used are given in Table 1.

Table 1. Electrical parameters of the power system

Parameters	Value
Frequency	50 Hz
Generator output voltage	14.6 kV
Transmission line voltage	154 kV
Desired active power	100 MW
Reactive power value	27 MVar

There are four types of faults: line-ground (A-G, B-G, and C-G), double-line-ground (AB-G, AC-G, and BC-G), line-line fault (AB, AC, and BC), and three-phase (ABC). Simulated by modifying the fault type restriction in the fault's module. Different fault data for L-G, LL-G, LL, and LLLL-G faults are created using the transmission line system's MATLAB software model. First, a multilayer feed-forward network is created. The number of hidden layers is properly raised to ensure the network's viability. The network was set up to establish the biases and weights of the network object, ready it for training. Training was done in batch mode, which produces fewer errors and is substantially faster.

The amount of validation checks, the size of the gradient performance, and the network performance were all important factors to consider while training the network. After training and validating the network, it can now be utilized to determine the relay system's reaction to various failure scenarios. The Neural Network software is then transferred to the microprocessor-based relay in place of the standard mathematical formulae. Figure 4 depicts the current waveform of an intact transmission line network before a failure, whereas Figure 5 depicts the current waveform of a damaged transmission line network following a fault generated from the system's MATLAB model. The data obtained from all fault situations was arranged into training sets using MATLAB software.

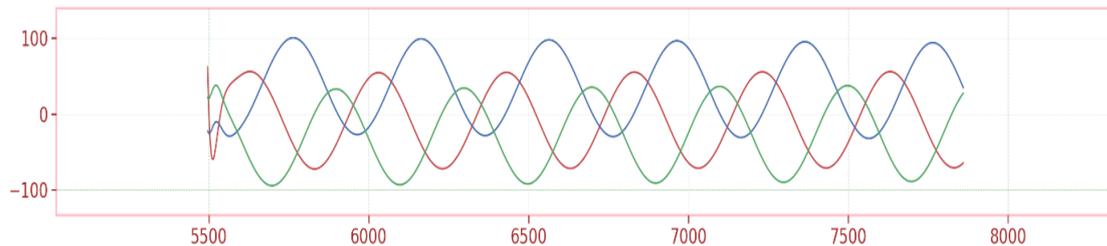


Figure 4. Fault-free Current Waveform

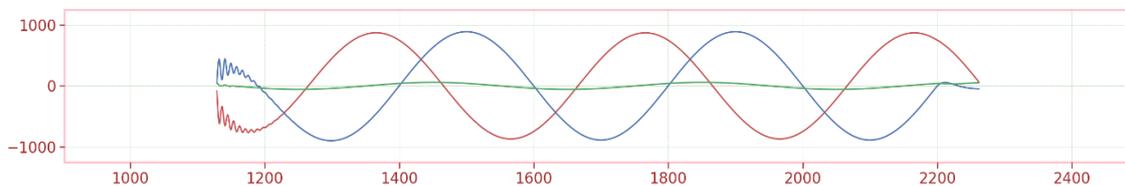


Figure 5. Fault Current Waveform

3.2. Dataset

The Electrical Fault Detection and Classification dataset on Kaggle was collected by Esathya Prakash and developed to detect faults in electrical power systems. This dataset is simulated to detect and classify faults in transmission lines of an electric power system.

The power system is simulated in MATLAB with 4 generators, each with an output voltage of 11×103 V, and transformers located in the middle of the transmission line. The system is operated under normal and various fault conditions, and the line voltages and line currents measured at the output side of the transmission line are collected, resulting in approximately 12,000 data points. These data are labeled so that fault detection and classification can be performed using artificial neural networks. The given dataset provides a basis for the accurate detection of various faults in the electrical power system and can be used for the rapid activation of system protection equipment.

An artificial neural network model designed to utilize three different machine learning and one deep learning algorithm is selected. Several experiments were conducted to determine the algorithm, activation functions, number of hidden layers and number of hidden neurons. This dataset contains scaled current and voltage values of three phases. There are 11 different fault conditions and no fault conditions for the 6 inputs in the data set. The truth table for these fault types is shown in Table 2.

Table 2. Truth table of various types of faults

	Fault type	A Line	B Line	C Line	Ground
1	A-G	1	0	0	1
2	B-G	0	1	0	1
3	C-G	0	0	1	1
4	A-B	1	1	0	0
5	A-C	1	0	1	0
6	B-C	0	1	1	0
7	A-B-G	1	1	0	1
8	A-C-G	1	0	1	1
9	B-C-G	0	1	1	1
10	A-B-C	1	1	1	0
11	A-B-C-G	1	1	1	1

The neural network used has scaled instantaneous voltages and currents of all three phases for five different fault conditions and for the fault-free condition. A total of 7,861 data points are labeled in the dataset. The number of faults in the system according to the fault type of these data are; 1134 A-B-G Fault, 1133 A-B-C-G Fault, 1129 A-G Fault, one A-B-C Fault, 1004 B-C Fault and 2365 No Fault. In addition, the numerical values of A, B, C and Ground Fault values in the data set are presented in Figure 6.

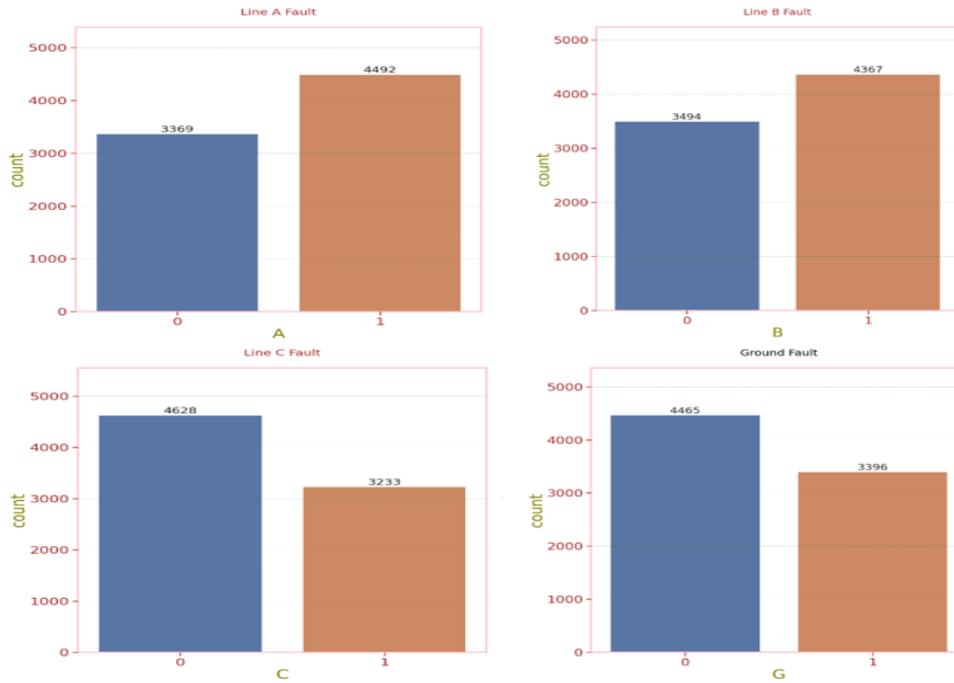


Figure 6. A, B, C and Ground Fault value

The dataset is randomly divided into two subsets for training and testing the models. The *Electrical Fault Detection and Classification* dataset, consisting of a total of 7,861 data points, is divided into the 75% training set and the 25% test set. This division was done to avoid overlearning of the models and to evaluate their generalization ability. A value of `random_state=42` was used to ensure the reproducibility of the study. Furthermore, a separate validation set was not explicitly allocated, but part of the training set was used for validation during model training.

3.3. Bagging classifier

Bagging (Bootstrap Aggregating) is a powerful ensemble learning method used in supervised learning algorithms and is widely preferred in classification tasks. Basically, multiple base classifiers are trained by randomly selecting samples from the training set. Each classifier is trained independently on its own subset and then the outputs of the classifiers are combined with techniques such as majority voting or weighted voting to make the final classification [22-23]. This method provides an effective solution, especially for algorithms with high variance and overfitting tendencies. Bagging increases the diversity of the model by training each base classifier on different training subsets, resulting in a more reliable and general model. This diversity strengthens the generalization capability of the model, resulting in more accurate and stable results across a variety of data sets.

3.4. AdaBoost classifier

AdaBoost is an ensemble learning method that combines weak classifiers or regression models to create a stronger and more generalizable model. In this approach, each model initially has low accuracy and is weighted by errors. Misclassified or predicted examples are focused on by giving more weight to subsequent models, so that each new model is trained to correct the errors of the previous model. This process of sequential addition gradually increases the accuracy of the model, building a strong ensemble. AdaBoost offers high accuracy, low tendency to overfit and robustness to noise in data sets, especially for classification and regression problems. However, accurate hyperparameter tuning is critical to the success of the model, as there is a risk of over-tuning. AdaBoost generally achieves effective results on large datasets, providing high generalization capability and flexibility [24].

3.5. Gradient boosting classifier

Gradient Boosting Classifier is an ensemble learning method that builds a stronger model by successively training weak classifiers. This algorithm ensures that each new model is added to correct the error margins of the previous models. At each step, Gradient Boosting optimizes the predictions of the new model by focusing on the errors of the previous model, thus trying to minimize the classification errors. This process ensures that each new model focuses predominantly on faulty predictions. Gradient Boosting is particularly well known for its ability to achieve high accuracy and often provides a robust model that can control the risk of overfitting [25]. However, the performance of the model depends on the hyperparameter settings and can run the risk of overfitting without proper optimization. Therefore, it is possible to achieve high accuracy and generalization power with appropriate parameter settings and tuning techniques.

3.6. Convolutional neural network

CNN is an artificial neural network architecture designed specifically for image processing and visual data analysis. CNN uses several consecutive layers to analyze the input data, including convolutional layers, pooling layers, and fully connected layers [26]. Convolutional layers preserve spatial relationships and produce feature maps by applying filters over small local regions to learn important features in the image. Pooling layers, on the other hand, reduce the computational burden by reducing the data size and enable the network to have higher generalization capability. Thanks to its ability to perform automatic feature extraction, CNN has the ability to learn from raw data without the need for manual feature engineering. This makes it an ideal tool for image classification, object detection, face recognition and many other computer vision applications. The success of CNN becomes more evident when trained on large data sets, because thanks to the deep layers, the network can effectively learn complex data and increase its generalization power.

3.7. Evaluation metrics

In the field of deep learning, performance metrics are a fundamental tool for evaluating and improving the effectiveness of models. These metrics provide important information to improve the success of models, identify errors and biases, and make accurate predictions. Often, accuracy is not the most appropriate metric in all cases when assessing the overall performance of the model. Instead, metrics such as precision and recall provide a more detailed analysis by examining the number of true positive predictions made by the model and the proportion of actual positive samples that are correctly identified. These metrics become more critical, especially in unbalanced data sets. Accuracy measures the proportion of predictions made by the model that are correct, while precision is the ratio of true positive predictions to all positive predictions. Sensitivity shows how many true positive samples are correctly predicted. The F1 score provides a more balanced assessment by taking the harmonic mean of precision and sensitivity. This metric is particularly useful in unbalanced data sets to analyze the success of the model in a fairer way. Mathematically, accuracy is the ratio of all correct predictions to total predictions, precision is the ratio of true positive predictions to all positive predictions, and sensitivity is the ratio of correctly predicted positives to true positives [27-28]. The F1 score balances these two metrics, taking both measurements into account and providing a more comprehensive assessment. Mathematical formulas for the evaluation metrics are given in Equations (1)-(4).

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Number of Total Prediction}} \quad (1)$$

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (2)$$

$$Recall = Sensitivity = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (3)$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

4. Experimental Results and Discussion

In this study, a set of powerful machine learning and deep learning methods is used to effectively detect and classify faults in transmission lines. Ensemble methods such as Bagging, AdaBoost and Gradient Boosting Classifier have played an important role in improving the accuracy and robustness of the model by combining basic classifiers to achieve accurate fault detection results. In addition to these methods, a CNN structure, which is successful in feature extraction and identifying complex fault patterns, was also used to distinguish between different fault types. The experimental results section evaluates the performance of these methods and discusses in detail the advantages and limitations of the models and their contribution to fault detection in electricity transmission systems. To better understand the structure of the data in the dataset, the correlation between each feature is calculated and visualized as shown in Figure 7.

The correlation matrix presented in Figure 7 shows the relationship between electric current and voltage (I_a , I_b , I_c and V_a , V_b , V_c) measurements. The correlation coefficient takes values between -1 and +1, with +1 indicating a perfect positive relationship, -1 indicating a perfect negative relationship, and 0 indicating no relationship.

Moderate negative correlations, such as -0.38 between I_a and I_b , -0.28 between I_a and I_c , and -0.53 between I_b and I_c , are observed. This indicates that the current phases have an inverse interaction with each other, i.e., when one increases, the other tends to decrease. There are high negative correlations of -0.51, -0.47, and -0.52 between V_a and V_b , V_a and V_c , and V_b and V_c , respectively. These correlations indicate that the different phase voltages are highly reversed with respect to each other. Low-level correlations are usually observed between currents and voltages. For example, I_a and V_a have a very low positive correlation of 0.033, while I_c and V_b have a low negative correlation of -0.096. This indicates that the current and voltage values are independent or weakly correlated between certain phases. Since there is no strong positive or negative relationship in this correlation matrix, most current and voltage values can be considered as independent. Especially in system modeling and fault detection, this independence or low correlation between phases indicates that the effect of events occurring in certain phases on other phases is limited.

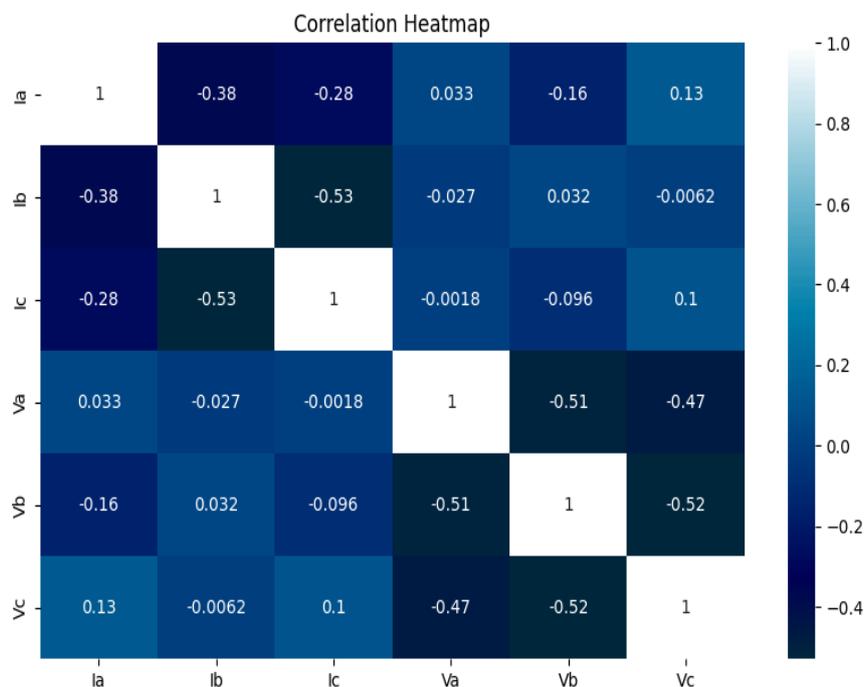


Figure 7. Correlation of all parameters

Hyperparameter optimization for machine learning algorithms has been performed using the Random Search method. Random search is an optimization technique that selects the best performing parameter set by trying

random combinations in the hyperparameter space. This method offers the possibility to efficiently explore a large hyperparameter space while reducing the computational cost. The optimization process was performed by trying 10 random combinations for each algorithm and using 5-fold cross-validation, which increases the generalizability of the models and reduces the risk of over-fitting. Table 3 shows the hyperparameter settings for Bagging, AdaBoost and Gradient Boosting Classifier used in the study. The proposed CNN model is given in Table 4.

Table 3. Parameters used for machine learning algorithms

Parameter	Classifier Models		
	Bagging	AdaBoost	Gradient Boosting
Number of estimators	50	50	100
Learning rate	0.1	1	0.1
Base estimator	5	1	3
Max depth	5	1	3
Subsample	-	-	0.8
Loss Function	-	-	Log Loss
Random state	50	50	50

The proposed deep learning model is designed for the binary classification problem and consists of fully connected layers. The first layer of the model is a hidden layer of 256 neurons with a ReLU activation function, which allows complex features to be extracted from the data. This layer is followed by a 0.5 dropout layer to prevent overlearning. The following layers again use ReLU activation with 128 and 64 neurons respectively. In both layers, a 0.5 dropout mechanism is applied to increase the robustness of the model to noise and to minimize the risk of overfitting. The output layer of the model is a single neuron with a sigmoid activation function that bounds the output between 0 and 1, generating a classification probability for each sample. The binary_crossentropy loss function was used to build the model; this function is very effective in measuring classification errors. Furthermore, the Adam optimization algorithm is used to update the parameters of the model quickly and efficiently.

Table 4. Parameters used for the proposed CNN model

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Number of Epochs	50
Loss Function	Binary Crossentropy
Activation Function	ReLU (hidden layers), Sigmoid (output layer)
Regularization	Dropout (rate = 0.5)

The training process was continued for 50 epochs, and the accuracy rate obtained from the validation data at the end of each epoch was carefully monitored. This method ensured that the model-maintained stability in the learning process and increased its ability to generalize. The success of the model is reflected in its ability to achieve high accuracy rates due to the careful configuration of its architecture and its ability to generalize to different data sets.

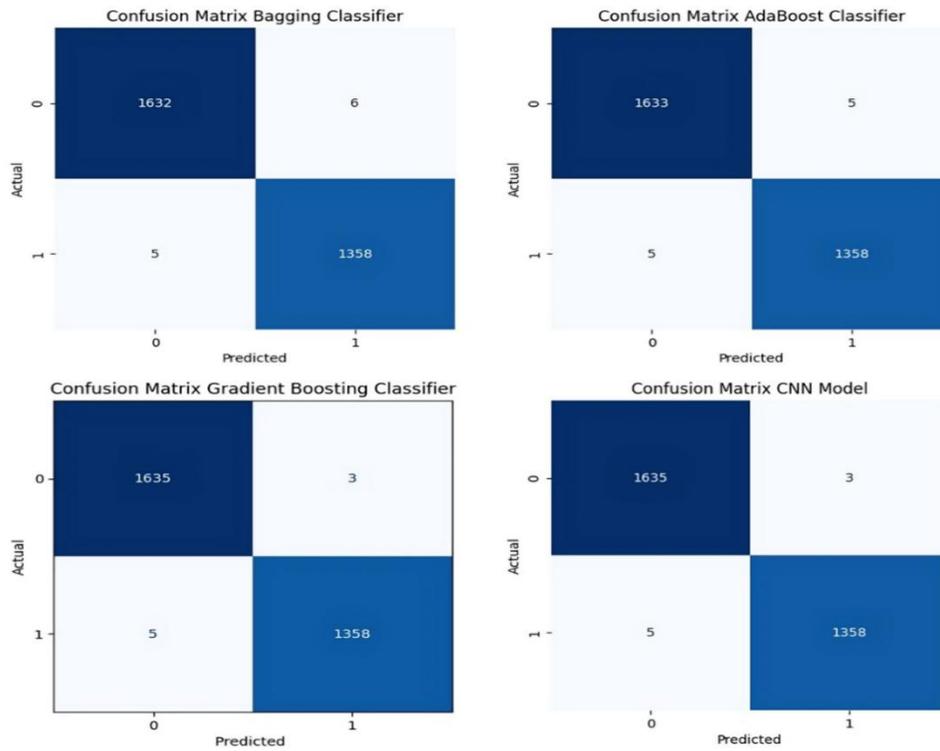


Figure 8. Confusion matrix of models

Figure 8 shows the confusion matrices of the models used. According to the results of the complexity matrix created to evaluate the accuracy performance of the four given models, all models achieved high accuracy rates, but there were some differences. Bagging Classifier performs relatively poorly with 6 false negatives and 5 false positives, while AdaBoost and Gradient Boosting Classifier and CNN models make fewer errors. The Gradient Boosting Classifier and CNN model showed the highest performance with only 3 false positives and 5 false negatives. This result shows that, in particular, the Gradient Boosting and CNN models offer the best accuracy performance, indicating that these models are suitable for fault detection.

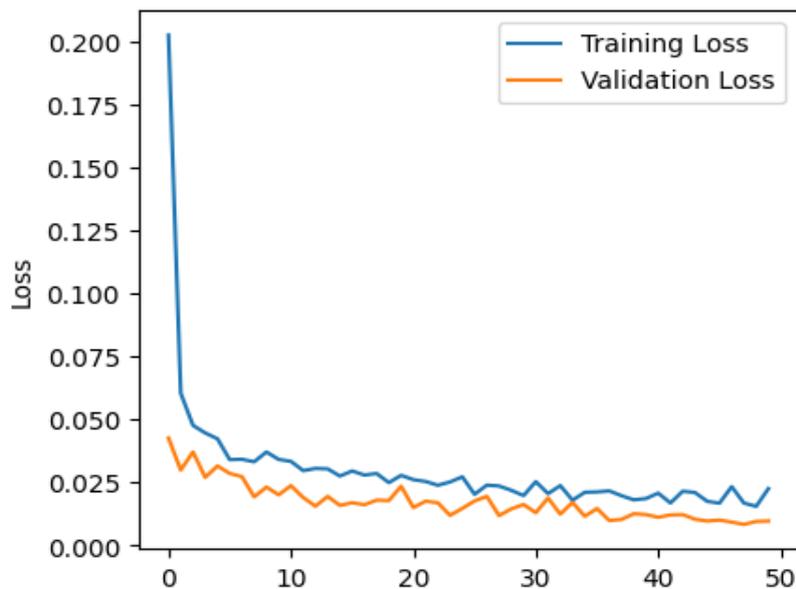


Figure 9. Loss graph of the proposed model

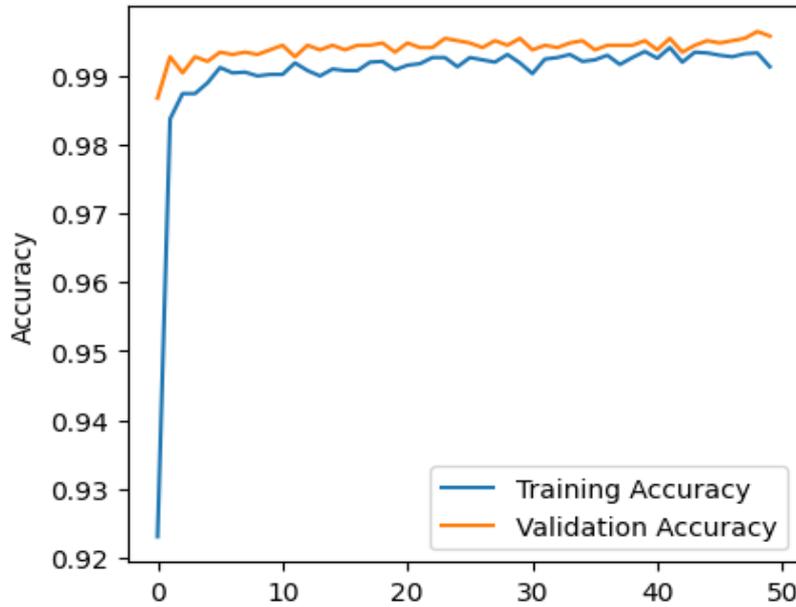


Figure 10. Accuracy graph of the proposed model

The graphs in Figures 9 and 10 show the variation of loss and accuracy metrics of our proposed model during the training process, respectively. On the left, the training and validation losses decrease and stabilize, indicating that the model learns successfully on both datasets. On the right, the accuracy rates, especially for the validation set, reach very high values from the beginning, with training accuracy of 99.19% and validation accuracy of 99.73% after 50 epochs. This shows that the model performs consistently and strongly on both training and validation data and does not overfit. The model's validation loss (0.0096) and training loss (0.0212) values confirm that the overall accuracy is quite high with low error rates. These results imply that the model learns from the training data while generalizing well to the validation data and functions as a high-performance classifier for electrical fault detection.

Table 5. Comparison of the results of all models

Model	Accuracy	Precision	Recall
Bagging	99.63	99.56	99.63
AdaBoost	99.66	99.63	99.63
Gradient Boosting	99.73	99.77	99.63
Proposed Model	99.73	99.77	99.63

Table 5 compares the performance of Bagging, AdaBoost, Gradient Boosting and the proposed model. According to the key performance metrics in the table, it is seen that all models achieve very high accuracy rates, with all of them achieving over 99%. In particular, Gradient Boosting and the Proposed Model exhibit the highest performance with an accuracy of 99.73%. As shown in Table 5, the performance metrics (accuracy, precision, and sensitivity) of the Proposed Model and Gradient Boosting are nearly equivalent. However, the main advantages of the Proposed Model over Gradient Boosting are as follows: First, thanks to its CNN-based structure, it can automatically extract spatial and temporal features from raw current-voltage data, thereby significantly reducing the need for manual intervention in the feature engineering stage. Second, the model's layered architecture offers higher generalization capabilities in complex and noisy data sets, which translates into a more robust detection mechanism against fluctuating signal conditions in real-time applications. Third, when GPU-accelerated optimization techniques are used during the training phase, training can be performed in a shorter time and with lower memory load, even on large-scale data sets. In addition, since the CNN model is deep learning-based, it effectively controls the risk of overfitting with regularization techniques such as Dropout layers and early stopping. Finally, the architecture of the proposed structure is highly adaptable for reuse with transfer learning or fine-tuning steps in different topologies and

dynamic system conditions, thus enabling more practical adaptation of the model to different transmission line configurations or future data varieties. These features demonstrate that the proposed CNN model is superior to Gradient Boosting not only in terms of numerical performance metrics but also in terms of ease of application, flexibility, and real-time performance.

In terms of precision, Gradient Boosting and the Proposed Model achieve the highest precision of 99.77%, while Bagging and AdaBoost models show slightly lower precision values. This means that Gradient Boosting and the proposed model provide higher precision with fewer false positives. In terms of recall, the value of all models is equal to 99.63%. This means that all models correctly classify true positives at the same rate. Overall, Gradient Boosting and the Proposed Model perform quite similarly in terms of accuracy, precision and sensitivity, with precision being the most important. If precision is the priority, Gradient Boosting or the Proposed Model is the best choice.

Table 6. Comparison with similar studies in the literature

Study	Architecture	Accuracy (%)
Fahim et al. [6]	Unsupervised Capsule Network (CNSF)	98.8
Vaish et al. [7]	Supervised and Unsupervised ML Techniques	97.2
Shakiba et al. [9]	Convolutional Neural Network (CNN)	99.1
Goni et al. [10]	Extreme Learning Machine (ELM)	99.53
Kanwal & Jiriwibhakorn [11]	Adaptive Neural-Fuzzy Inference System (ANFIS)	98.8
Proposed Model	Convolutional Neural Network (CNN)	99.73

Table 6 shows the performance rates of the model proposed in this study compared to similar studies in the literature. When examining the studies in the literature, the CNSF model developed by Fahim et al. [6] achieved 98.5%, both supervised and unsupervised machine learning techniques used by Vaish et al. [7] achieved 97.2%, the CNN model proposed by Shakiba et al. [9] achieved 99.1%, the ELM model developed by Goni et al. [10] achieved 99.53%, and the ANFIS model used by Kanwal Jiriwibhakorn [11] achieved 98.8%.

The model proposed in this study achieved a success rate of 99.73% using a CNN-based approach. This rate indicates a higher level of accuracy than all other models in the table. The success rate of 99.73% achieved by the proposed model clearly demonstrates the effectiveness of the model and its superiority over other approaches in the literature, especially in the critical area of transmission line fault detection. This result shows that the proposed CNN model outperforms both previous CNN-based studies and various methods. Figure 11 shows the success rates of similar studies in the literature.

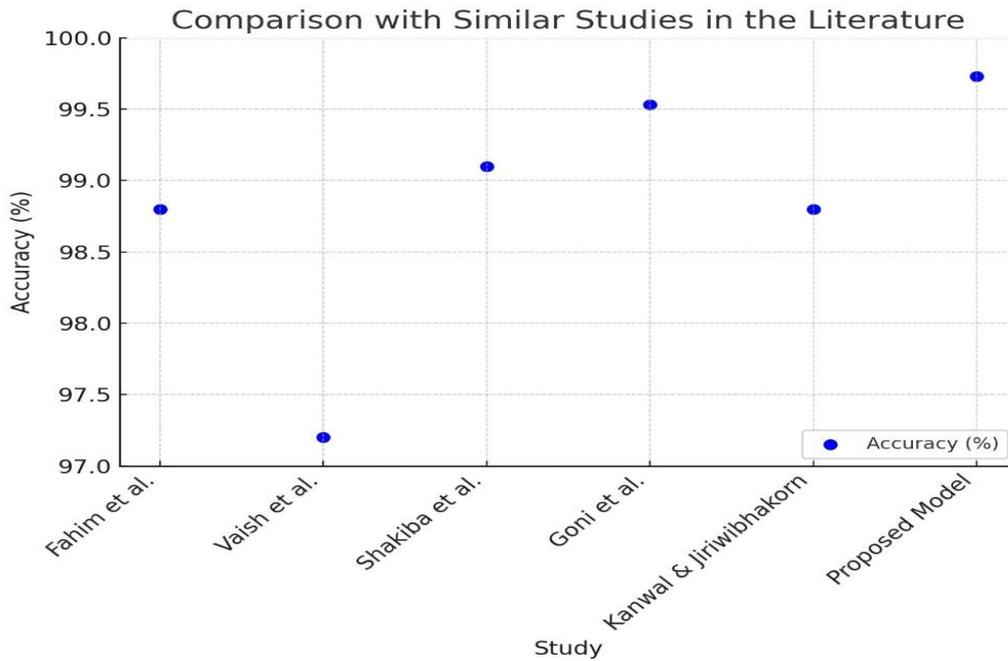


Figure 11. Comparison of the success rates of similar studies in the literature.

The proposed model offers significant advantages with high accuracy rates and efficient error detection. However, the model also has some limitations and potential drawbacks. As a deep learning-based model, it requires large data sets, which increases the overhead of data collection and preprocessing. Although the risk of overlearning is mitigated by dropout layers, this risk remains, especially for small datasets. In addition, the robustness of the model to different types of failures and noisy data has not yet been tested, requiring an evaluation of the model's performance in real-world conditions. These limitations may limit the effectiveness and generalizability of the model in practical applications.

In industrial applications, the challenges faced by the proposed model include limited data access, real-time processing requirements and system integration. To overcome these challenges, it is recommended to develop real-time data acquisition systems and apply optimization techniques to reduce the computational burden of the model. In addition, the scalability of the model should be evaluated by testing it on large power systems, which requires optimization of training time and resource utilization. Adaptability to different power system topologies can be achieved by retraining the model with larger data sets obtained from different system configurations.

5. Conclusion

In this study, machine learning algorithms are used to identify and classify faults in electricity transmission lines. The performance of Bagging, AdaBoost, Gradient Boosting, and CNN models is compared, and the success rates of each model in fault detection are analyzed in detail. According to the results obtained, the methods used provided high accuracy in fault detection, with the CNN model showing the highest performance. The proposed CNN model supports energy continuity by enhancing the system's ability to detect faults quickly and accurately with an accuracy rate of 99.73%, while ensemble ML methods provide consistent results in classifying different types of faults. This has the potential to reduce economic losses by optimizing maintenance processes. This shows that deep learning methods are successful in fault detection in transmission lines. In addition, hyperparameter optimization was applied to improve model accuracy, and the performance of different algorithms in this process was analyzed. The results are particularly valuable for the early detection of faults and the determination of appropriate response methods. These approaches can improve the reliability and efficiency of power transmission systems and prevent potential losses. The findings of the study provide a basis for preventing failures and optimizing the maintenance of transmission lines. The success rates obtained show that such approaches can be used in industrial applications and provide a strong basis for future studies. In this context, it is recommended that future studies should be supported

with larger datasets, a more detailed classification of different fault types, and the integration of other machine learning algorithms into the process. This study demonstrates that machine learning-based solutions can be effectively used in the maintenance and management processes of energy transmission lines and contributes to the development of innovative and effective fault management strategies for engineers working in the energy sector.

6. Author Contribution Statement

The authors contributed equally to the article.

7. Ethics Committee Approval and Conflict of Interest Statement

In the prepared manuscript, there is no need for ethics committee approval. The prepared manuscript has no conflicts of interest with any individual or institution.

8. Ethical Statement Regarding the Use of Artificial Intelligence

No artificial intelligence-based tools or applications were used in the preparation of this study. The entire content of the study was produced by the author in accordance with scientific research methods and academic ethical principles.

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