Development of an Intelligent Fault Detection and Calassification System for Power Grids using Artificial Neural Network

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Abstract: This research addresses the problem of faults in modern electrical grids, which cause power outages, reduced system stability, and financial losses. With the increasing sophistication of power systems due to their integration with artificial intelligence technologies, fault detection methods have become more efficient and effective. This paper proposes intelligent fault detection methods based on supervised deep learning techniques. These methods involve collecting existing electrical gauges from the power system, preprocessing the data, and applying a classification model to differentiate between normal and fault states. The model is trained using classified voltage and current datasets to enhance detection accuracy. Experimental results demonstrate that the proposed method achieves higher accuracy and faster fault detection compared to traditional methods. Its adoption enables efficient handling of large datasets, providing a scalable solution that can be integrated with other technologies to make real-time fault monitoring in smart grids more effective. Overall, this study highlights the importance of using intelligent technologies to improve the performance and safety of modern power systems.
Keywords: power systems, real-time fault, electrical gauges.

1. Introduction

One of the most important elements of modern society is the electrical power grid. The development of infrastructure is reflected in the provision of sustainable electricity across various sectors, including military, commercial, agricultural, and residential applications [1], [2].

The significant challenges facing developers is ensuring a continuous and highly stable electrical operating system to guarantee business continuity and sustain economic growth. Despite its importance, power grids are constantly subject to outages due to various types of faults, such as insulation failure, breakage, and exposure to different environmental conditions. These faults can lead to sudden power cuts and, consequently, instability of the electrical grid[3].

Fault detection and identification are crucial functions in advanced power grids, as they help identify faulty or defective components and quickly isolate them from the rest of the network. Early fault detection minimizes damage to the system, ensures safe operation, and reduces the costs of component replacement and maintenance. Traditional fault detection methods primarily rely on mathematical calculations and equations, along with manual inspection techniques. Although these methods are widely used, they are time-consuming and labor intensive, with low fault detection accuracy and difficulties in handling the large datasets generated by modern, large-scale smart grids[4].

In recent years, artificial intelligence (AI) technologies have witnessed significant development across various fields, including applications for protecting and monitoring electrical grid systems[5]. This is due to the ability to analyze massive datasets and identify hidden patterns with high efficiency using AI techniques. Artificial neural networks are among the most effective methods for classifying and predicting conditions [6]. They enable models to learn and mimic the human brain, enabling them to learn the relationship between electrical measurements, such as voltage and current signals, when the grid experiences various faults[7] .

This research paper presents a system for detecting and classifying faults in power networks using artificial neural networks. The proposed system aims to detect various fault conditions affecting the network based on electrical measurements collected from the power system. The artificial neural network model was trained and tested on datasets to achieve high classification accuracy and high-precision performance. The developed system is expected to improve fault diagnosis methods, increase efficiency, and reduce detection and resolution times, thus providing a more advanced and effective system

2. Related Research

This section presents previous research and studies related to the classification of faults in electrical networks. It will highlight the importance of technologies in detecting conditions affecting various networks and the impact these technologies have on the operating system.

Samantaray. [8] presents a decision tree-based method for fault location and classification (distinguishing whether the fault occurs before or after TCSC /UPFC. This is achieved using a set of current and voltage samples after the fault as inputs. The models were trained and tested under various conditions, including fault type, fault impedance, source impedance, fault onset angle, and load variations. Using data from 16,800 TCSCs and 25,600 UPFCs, the model achieved high accuracy: up to 98.8% for TCSCs and 98.5% for UPFCs. The decision tree algorithm outperformed other algorithms in terms of accuracy and detection speed. It also demonstrated more reliable performance under environmental conditions such as noise.

Turanlı et al. [9] described the design of a deep learning model built for classifying faults in electrical power transmission lines using real, generic, and synthetic datasets to improve fault detection and classification accuracy and reduce downtime. The data were obtained from Gediz Electric (Turkey). The generic dataset was generated using MATLAB Simu, and the synthetic dataset was obtained through Simulink modeling. Each dataset was divided into categories such as line-to-ground and three-phase faults. The model was built using the Keras/TensorFlow environment and multiple convolutional units with residual links. The Adam optimizer, categorical cross-entropy loss, 100 training cycles, and a batch size of 32 were used. Various metrics were employed, including accuracy, fine-tuning, recall, F1 metric, ROC curves, and area under the curve (AUC). The results showed high accuracy across all datasets (ranging from ~0.98 to 1.0).

Yadav et al. [10] presented the detection, classification, and locating of faults in modern power grids using Artificial Neural Networks (ANNs) and Adaptive Fuzzy Neural Inference Systems (ANFIS). While ANNs learn fault patterns from data, they require more training and are affected by various conditions. ANFIS, however, combines neural learning with fuzzy logic, making it more adaptable, interpretable, and accurate. Both networks were tested on an 11 kV power transmission model using MATLAB simulation. The ANNs achieved higher accuracy (92-95%) compared to ANFIS (97-99%) in terms of faster fault detection, better classification of fault types (line-to-ground, line-to-line, three-phase), and more precise fault location. The ANN system was effective but less accurate, exhibiting a slight error in fault location.

Alowaidi et al. [11] based on a Convolutional Deep Belief Network (CDBN) was developed for automated fault detection in the Hydroelectric Power System (HEPS). Because traditional fault detection methods are reactive and involve significant human intervention, a model combining Convolutional Neural Networks (CNNs) and Deep Belief Networks (DBNs) was developed to improve early fault detection and identification. The model was integrated with pressure, load, and temperature sensors to collect data from two Chinese stations, totaling 3.3 million samples, which were divided into training and testing phases. Faults were categorized as sudden, catastrophic, minor, and mild. The model achieved high prediction accuracy using a set of measurements: accuracy, fine-tuning, recall, and F1 metric.

3. Methodology

The essential steps in the proposed system methodology include collecting data to create a dataset and building a model. After that, the model is trained to classify wheat leaves and obtain the best results.

3.1 DatasetCollection

The first step in the process is to prepare the dataset for use in the next step. The data was obtained from the Kaggle platform for detecting and classifying electrical faults in power systems. The dataset was created using MATLAB/Simulink by simulating various conditions and faults that can affect electrical transmission networks. The main objective of the dataset is to provide diverse electrical values that can be used to train models on different patterns to create an intelligent system for the automatic and rapid detection and classification of electrical network faults.

The dataset consists of measurements obtained from a three-phase power network. These parameters include voltage and current measurements. The input characteristics used in this work are six electrical measurements: Va, Vb, and Vc for the voltages of phases A, B, and C, respectively, and Ia, Ib, and Ic for the currents of phases A, B, and C as show in table 1. These values change continuously with each power network operation and with each fault change in the system.

Table 1: Three Phase Electrical Parameters

parameters	Phase	Feature
Voltage	Voltage of Phase A	Va
Voltage	Voltage of Phase B	Vb
Voltage	Voltage of Phase C	Vc
Current	Current of Phase A	Ia
Current	Current of Phase B	Ib
Current	Current of Phase C	Ic

The dataset contains several categories, each representing a common type of fault that occurs in the electrical power grid. The normal category represents trouble-free operation. A line-to-ground (LG) fault represents a short circuit between a single transmission line and the ground. A line-to-line (LL) fault occurs when two lines are connected together due to an insulation failure or other causes. A double-line-to-ground (LLG) fault represents two transmission lines being connected to the ground simultaneously. A three-phase (LLL) fault is a symmetrical fault that affects all three phases simultaneously and is considered one of the most dangerous faults in electrical power grids,as show in table 2.

Table 2: Fault Classification

Class	Description
Normal	Normal condition
LL	Line-to-Line fault
LLL	Three-Phase fault
LG	Line-to-Ground fault
LLG	Double Line-to-Ground fault

3.2 Dataset Preparing

Before training the artificial neural network (ANN) model, the dataset underwent preprocessing to improve the quality of the input data, which in turn enhances the model's performance accuracy. This preprocessing included organizing the dataset, addressing missing values, and converting categorical fault classifications into numerical values suitable for the training algorithms. After preprocessing, the dataset was divided into three sets for training, verification, and testing, with percentages of 70%, 15%, and 15% as show in table 3, respectively. The training dataset was used to train the ANN model on voltage and current readings, while the verification dataset was used to continuously monitor the model's performance during training and verify its efficiency. Finally, the test dataset was used to evaluate the model's final performance and its ability to classify faults on new and previously unseen data. The number of sample in each class is 100 and the total number of dataset is 500.

Table 3: Dataset Division.

Dataset Division	Division
Training Set	70%
Validation Set	15%
Testing Set	15%

3.3 Building and Training Models

To classify faults in electrical networks, an artificial neural network (ANN) model was trained on a set of data consisting of voltage and current measurements. This allowed for the classification of fault types. The ANN model was chosen for its ability to train on nonlinear relationships between electrical measurements and different fault types, resulting in very good classification accuracy. The model was implemented using supervised learning, a type of learning where training is conducted under the guidance of a teacher, using previously obtained classified fault data from the measurement set.

The ANN consists of several layers, beginning with an input layer. This input layer comprises input cells representing the specific electrical measurements of the system, including the voltages of phases A, B, and C (Va, Vb, and Vc) and the currents of phases A, B, and C (Ia, Ib, and Ic). These parameters were used in the input process because they contain important values about the operating state of the electrical network. Significant changes in these values lead to faults.

A set of hyperparameters was used to train the model for fault classification. The ReLU (Modified Linear Activation Unit) activation function was implemented to reduce computational complexity and improve the deep neural network's learning and classification capabilities. To optimize the training process, the popular Adam optimizer with a learning rate of 0.001 was used. Adam was chosen because it adaptively modifies weight values as needed, resulting in accurate weight adjustments and stable training performance. The categorical cross-entropy loss function was used to measure the difference between the expected values and the actual fault classifications during training. The data using batches size of 32, and 100 epochs, as show in table 4.

Table 4: Training Parameters

hyperparameter	value
Activation Function	ReLU
Optimizer	Adam
Learning Rate	0.001
Loss Function	Categorical Crossentropy
Batch Size	32
Epochs	100

3.4 Models Evaluation

This section presents the most common equations and metrics used to evaluate the performance of a model trained to identify and detect faults in electrical networks, and to determine the accuracy of the process:

The confusion matrix, accuracy, F1 metric,precision, and recall are key metrics for determining a system's fault classification efficiency. It's important to note that these metrics are equations consisting of values representing true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

- Confusion Matrix: This matrix displays the model's performance to help understand where prediction errors occurred. The matrix consists of columns and rows, the rows show the correct classification cases, the columns show the predicted classification cases, and the errors are displayed as values (see Fig 1).

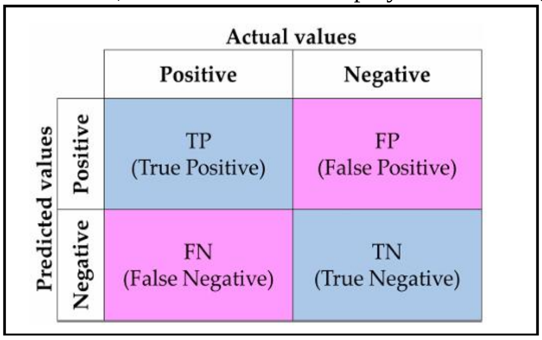

Fig 1: Confusion Matrix[12].

- Recall: expresses the return of correctly predicted positive cases that were successfully identified [13].As shown in the following equation:

$$Recall = \frac{TP}{TP+FN} \qquad (1)$$

- Precision: This accuracy demonstrates how well the model detects positive cases[14] , as illustrated in the following equation:

$$Precision = \frac{TP}{TP+FP} \qquad (2)$$

- Accuracy: This is one of the most important metrics used to evaluate performance, representing the number of data points that were predicted correctly [15], as in the following equation:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \qquad (3)$$

- FI-score:is used to evaluate model performance, combining two measurementsprecision and recall.It is useful when there are issues requiring adjustments between accuracy and recall [16], as illustrated in the following equation:

$$FI\ score = 2 \times \frac{Precision\ \times Recall}{Precision\ + Recall} (4)$$

4. Results

The proposed model was trained using a pre-prepared dataset representing voltage and current measurements from the electrical grid system. The model's primary objective was to classify faults occurring in the electrical power transmission network based on current and voltage measurements. During the training process, the artificial neural network model learned the relationship between electrical parameters and the faults they cause. This process was repeated by adjusting weights using a backpropagation algorithm to ensure optimal results.The model underwent 100 training cycles at a learning rate of 0.001 with the Adam optimizer and a batch size of 32 samples. During training, both the training accuracy and verification accuracy gradually improved, reaching optimal results, while the loss values continuously decreased to the lowest possible values. This indicates stable learning behavior and the model's successful learning.The results and testing demonstrated that the proposed network model achieved high classification in detecting and classifying electrical faults. The model successfully distinguished between normal operating conditions and different fault categories based on changes in voltage and current measurements.

After training the model the final evaluation of the model show high accuracy in classifying various faults affecting electrical networks, reaching an accuracy of 88.8%. This indicates the model's ability to correctly detect the majority of samples, and this accuracy is reflected in its very successful extraction of latent patterns from the input data, which represents current and voltage measurements.The evaluation was performed using a confusionmatrix(see Fig 2)., precision, recall, and the FI-score,as show in table 5, to assess the effectiveness of the proposed model.

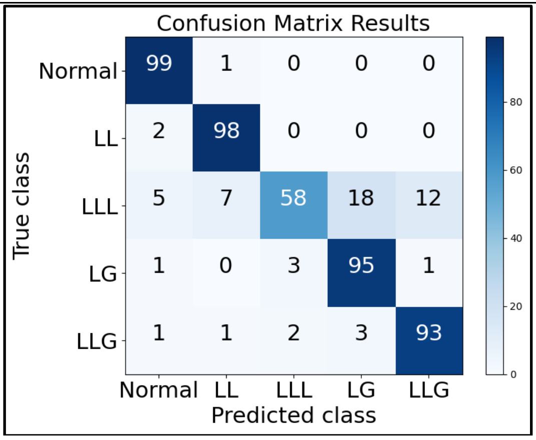

Fig 2: Confusion Matrix Results.

Table 5: Model's Result.

Classes	FI-Score	Recall	Precision
Normal	95.1%	98%	91.7%
LL	94.70%	97%	91.2%
LLL	72%	59%	92%
LG	88%	95%	81.9%
LLG	90%	94%	88%

5. Conclusion

After data collection, preparation, and model training, the proposed artificial neural network model demonstrated efficient and effective performance in detecting and classifying faults in electrical networks. Based on the confusion matrix in Fig 2, the model effectively predicted positive states, indicating its ability to learn the relationship between voltage, current, and different fault states for each measurement.

The results show that the artificial neural network model achieved high accuracy in detecting fault states, particularly in categories one and two, achieving high accuracy and recall values exceeding 93%. This indicates that the electrical relationship associated with these two fault categories was clearly detectable and distinguishable, allowing the model to classify them correctly with only minor misclassification errors.

Categories four and five also performed well, with high recall rates and F1 scores. The model successfully identified most cases in these two categories, reflecting the effectiveness of the preprocessing and preparation methods used during the training phase. However, Category 3 exhibited lower performance compared to the other categories. The recall value for this category was approximately 59%, indicating that some samples within Category 3 were misclassified into other fault categories due to the similarity between their electrical characteristics and those of the remaining categories, particularly 4 and 5.

Confusion matrix analysis clearly shows that the artificial neural network model exhibits inconsistent results between Category 3 and adjacent fault categories during fault occurrence. Despite this, the model achieved acceptable accuracy for Category 3, demonstrating its reliability in predicting this category.

The preprocessing phase and the balanced distribution of the training and testing dataset significantly improved the model's performance and mitigated the problem of bias towards specific categories. Implementing the proposed system using Google Colab created an efficient environment for training and testing the artificial neural network due to the presence of a graphics processing unit (GPU). This reduced computational complexity and resource utilization, while also improving the training process.

Overall, the intelligent system demonstrated high capability in fault detection and classification for electrical network applications. Although the presence of some fault categories presents a challenge due to the overlap of electrical characteristics, the final results demonstrate the effectiveness of artificial neural network models in smart energy system monitoring applications.

6. Acknowledgements

I extend my sincere thanks and appreciation to all those who provided support and contributed to the completion of this work. This also includes thanks to the donors and institutions that provided assistance, without which this research would not have been possible through the provision of facilities and technical resources.

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