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RESEARCH ARTICLE

Development of Disturbance Type Detection Using Convolutional Neural Network for Fault Signature Analysis

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Abstract

The rapid advancement of technology in electrical systems has led to increased complexity in power systems, making the operation and maintenance of power system networks more challenging, especially when disturbances occur. To address this issue, it is essential to maximize the utilization of available tools to effectively manage power system networks. Currently, power system networks are equipped with protection relays and control devices that provide various types of data about the system, such as the Disturbance Fault Recorder (DFR), which monitors and records the system's characteristics during network disturbances. The DFR stores information about system parameters during a fault; however, it is unable to identify the type or cause of the disturbance.Therefore, this paper proposes a method based on the Convolutional Neural Network (CNN) model to analyze DFR data and determine the type or cause of the disturbance, enabling more appropriate and effective follow-up actions. Based on the research findings, the CNN model, applied to six types of disturbance classification, achieved an accuracy of 93.87%. These results demonstrate that CNN, particularly using the VGG19 architecture, performs satisfactorily in analyzing graphical disturbance patterns.

Keywords: Convolutional Neural Network, Disturbance Recorder, Power Transmission, Fault Signature, Digital Fault Recorder

1. Introduction

In recent years, power transmission systems have become increasingly complex due to the integration of advanced technologies and the growing demand for reliable electricity. In the event of a system disturbance, the rapid and accurate classification of faults is essential for effective post-disturbance analysis and timely restoration of the power supply. Information regarding the type of fault plays a crucial role in determining the fault location and guiding the implementation of appropriate corrective actions. Accurate fault classification enhances the effectiveness of fault diagnosis systems by enabling the selection of the most appropriate fault location methodology [1]. There are various types of faults, including the High Impedance Fault (HIF). Prolonged operation under High Impedance Fault conditions can lead to an increase in temperature at the fault point, damage equipment insulation, trigger phase-to-phase or phase-to-ground faults, cause fault propagation, harm the surrounding environment, and even pose serious electrical hazards to personnel [2]. Therefore, comprehensive equipment is required to ensure the reliability and efficient operation of power systems, particularly within secondary systems such as protection and control devices. With the advancement of technology, protective relays have undergone significant development, one of the most critical features being the Disturbance Recorder. This component plays a vital role in capturing system behavior during faults and supports accurate decision-making in fault analysis and system recovery.

Conventional fault diagnosis relies on model-based techniques and requires domain experts to monitor the power grid. However, recent advancements advocate adopting Machine Learning (ML) paradigms to detect, classify, and localize faults, enabling rapid mitigation and ensuring reliable power supply [3]. Several methods employing Artificial Intelligence (AI) have been utilized, such as in [4], such as those that consider system stability using the Random Forest method; however, these approaches do not perform fault signature analysis, in [5], which have performed fault classification using machine learning techniques such as K-Nearest Neighbor (K-NN) and Random Forest (RF). These methods have demonstrated promising accuracy in distinguishing different types of faults under various operating conditions.

Nowadays, Convolutional neural networks are starting to be used in electricity. Such as being used to analyze transmission disturbances such as in [6], where CNN is used to distinguish between normal and disturbed conditions; in [7], it is used to predict the State of Charge on lithium-ion batteries; in [8] it is used to design motor drive controls. Convolutional Neural Networks (CNNs) are highly effective for analyzing fault signatures in power transmission lines due to their superior ability to detect and recognize patterns within complex data. This is particularly relevant for time-series data or visual representations of signals, such as wavelet transforms, spectrograms, or phasor diagrams. CNNs offer several key advantages, including automatic feature extraction, multidimensional data analysis, robustness against noise, fast and real-time detection, high classification accuracy, and flexibility in handling various data formats. These capabilities make CNNs highly relevant and powerful for fault detection in power transmission systems, as they can efficiently learn complex signal patterns, operate with low latency, and deliver high accuracy. As a result, CNNs are well-suited for integration into intelligent fault diagnosis systems in modern power networks, including Smart Grids.

However, their focus is primarily on fault type identification without a deeper analysis of fault signatures, such as waveform characteristics or transient behaviors, which are crucial for high-resolution fault diagnosis and root cause analysis in [9]

Using Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) for fault classification, in [10] which methods using Kernel Wavelet have been applied solely for fault location purposes, in [11] which The Firefly Algorithm and Linear Programming methods have been employed to determine Directional Overcurrent Relay (DOCR) coordination in response to faults, without identifying the specific fault types involved, in [12] used fuzzy and decision trees to determine the configuration. Compared with another, ResNet50 slightly outperforms the custom CNN in terms of accuracy and F1-score (0.94 for ResNet50 and 0.93 for CNN Custom), but requires significantly more training time (141s for ResNet50, and 85s for CNN Custom)[13]. GoogLeNet also performs competitively (0.91 for F1 Score and 125s for Training Time) but has a deeper architecture that introduces complexity[14]. On the other hand, traditional classifiers such as SVM and RF exhibit lower performance (0.84 and 0.82 for F1-Score), especially in spatial pattern recognition, which supports the well-established claim that CNN-based models are more suitable for image-based tasks[15].

The operation of the power grid relies heavily on devices that monitor, control, and protect power system networks. One such device is the Disturbance Fault Recorder (DFR), which captures current and voltage waveforms during disturbance events. While the DFR provides valuable data for assessing the characteristics of a disturbance, it does not have the capability to identify the type or cause of the disturbance. However, this information is crucial for effective power system operation and decision-making. For instance, identifying the type of fault enables operators to take appropriate follow-up actions. If the disturbance is caused by lightning, it may be necessary to improve the grounding of transmission towers and optimize the protection angle. If animals are the cause, installing deterrent devices becomes essential. In the case of disturbances caused by foreign objects such as kites, outreach and awareness campaigns for nearby residents are needed. Additionally, if vegetation is the source, targeted monitoring and maintenance in affected areas must be carried out.

Traditionally, the fault classification process relies on the expertise of trained personnel, which may not always be available in a timely manner. This manual approach can also be time-consuming, despite the urgent need to restore normal operations swiftly. Therefore, accurate and prompt identification of disturbance types is critical to enabling efficient and timely system restoration.

This paper presents a model for analyzing fault signatures obtained from Disturbance Fault Recorder (DFR) data, capable of distinguishing between various causes of power system disturbances. The proposed model processes DFR images and classifies them into several categories based on the disturbance type, such as lightning, foreign objects, broken conductors, and others. The model is developed using a Convolutional Neural Network (CNN), a method widely recognized for its effectiveness in image processing and computer vision tasks. The structure of this paper is as follows: Section 2 describes the development of the CNN-based fault signature analysis model. Section 3 presents and discusses the experimental results. Finally, Section 4 provides the conclusions drawn from this research.

2. Convolutional Neural Network Model Development

2.1 Disturbance Fault Recorder

The Disturbance Fault Recorder (DFR) is a device that records the events that occur in a power network. Faults and disturbances data can be retrieved from DFRs, which generate a unified COMTRADE file. This file is critically important for engineers and technicians in analyzing fault events and system disturbances [16]. Each disturbance recorded by the DFR contains a fault signature as an image representing the system's characteristics during an event in the power system.

The Disturbance Fault Recorder (DFR) captures voltage signals (VA,VB,VC,VN) and current signals (IA,IB,IC,IN) at a system frequency of 50 Hz, utilizing a sampling rate of 128 samples per cycle. DFRs can be categorized into two types based on their installation: internal DFRs, which are integrated within Intelligent Electronic Devices (IEDs) such as protective relays, and external DFRs, which function as standalone units. An example of a DFR recording is illustrated in Figure 1, where the current (depicted in blue) and voltage (depicted in red) waveforms at a specific location in the power system are shown over a given time interval.

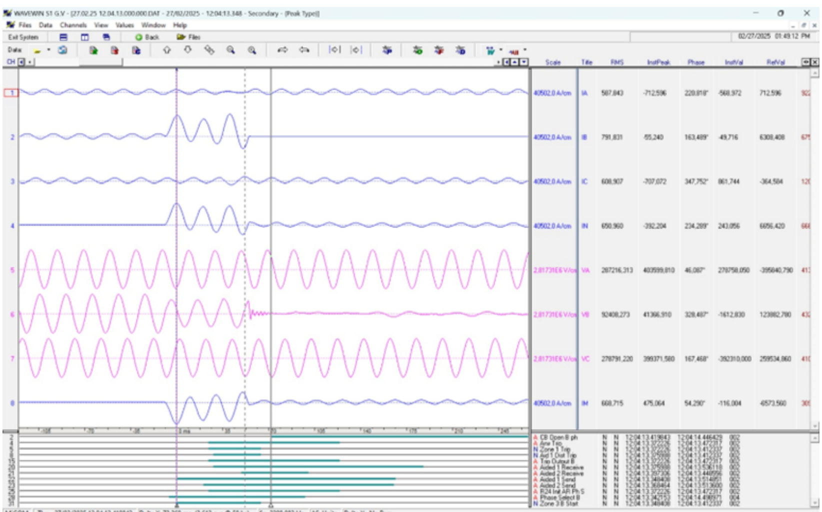

Figure 1. A Example of Disturbance Fault Signature Snapshot

Despite providing valuable information on current and voltage characteristics during fault conditions, the Disturbance Fault Recorder (DFR) is not capable of identifying the underlying cause of the disturbance. However, the recorded fault signatures contain patterns that can be analyzed to infer both the type and cause of the disturbance. Such fault signature analysis can support more accurate diagnosis and facilitate appropriate repair and corrective actions, thereby enhancing the reliability and responsiveness of power system operations.

2.2 CNN Model Development for Fault Signature Analysis

CNN is a machine learning algorithm, quite similar to the well-known artificial neural network (ANN), that is mostly used for image processing in computer vision. CNN is powerful for analyzing data that can be structured into grid-like matrix, such as images or videos. It processes the data by analyzing the features via kernel optimization through multiple perceptrons. The Convolutional layer mainly uses multiple Convolutional kernels to extract features from input data. Considering that the input is a two-dimensional matrix, the two-dimensional Convolutional method is used in the Convolutional layer [17]. A hybrid Convolutional network defines a coordinate system on a graph and expresses the relationship between nodes as a low- dimensional vector in the new coordinate system. At the same time, the hybrid convolutional network defines a cluster of weight functions, which act on all neighboring nodes centered on a node, and its input is the relationship representation between nodes (a low-dimensional vector), and its output is a scalar value [8].

A Neutral Network receives input from a single vector and transforms it through a series of hidden layers. Each Hidden Layer comprises a set of neurons, where neurons are fully connected to all neurons in the previous layer. Three primary layers are used to build ConvNets architecture: The Convolutional, pooling, and fully connected layers.

The Convolutional layer accepts a volume with the dimension of $W_1 \times H_1 \times D_1$, and requires four hyperparameters such as K (Number of filters), F (Spatial extend), S (Stride), and P (Amount of zero padding). From the input, the Convolutional layer will produce a volume of size $W_2 \times H_2 \times D_2$, where:

$$W_2 = \frac{W_1 - F + 2P}{S + 1} \tag{1}$$

$$H_2 = \frac{H_1 - F + 2P}{S + 1} \tag{2}$$

$$D_2 = K \tag{3}$$

The pooling layer accepts a volume size $W_1 \times H_1 \times D_1$ and only requires two hyperparameters: F (Spatial extend) S (Stride). From the input pooling layer will produce a volume of size $W_2 \times H_2 \times D_2$, where:

$$W_2 = \frac{W_1 - F}{S + 1} \tag{4}$$

$$H_2 = \frac{H_1 - F}{S + 1} \tag{5}$$

$$D_2 = D_1 \tag{6}$$

Three layers became less popular because their contribution has been shown minimal across various types of normalizations. Neurons in the fully connected layer are connected to the previous layer, similar to a regular neutral network.

The weight matrix would be large and mostly filled with zero for any CONV layer in the FC layer, except in specific blocks due to local connectivity. Within these blocks, many weights are identical due to parameter sharing. Consider a ConvNet architecture that takes a 224x224x3 image and processes it through a series of CONV Layer and Pool layers to reduce the volume of size 7x7x512. This reduction is achieved by applying five pooling layers, each halving the spatial dimensions, resulting in a final size of 7 (224/2/2/2/2/2 = 7). We can convert each of these three FC layers to CONV layers as described above: Substitute the first FC layer that looks at [7x7x512] volume with a CONV layer that uses filter size F=7, resulting in an output volume [1x1x4096]. Next, replace the second FC layer with a CONV layer that uses filter size F=1, producing output volume [1x1x4096]. After that, similarly replace the last FC layer with F=1, giving a final output [1x1x1000].

In this study, there is input in the form of images that will be processed using CNN with output in the form of classification results of 6 types of causes of disturbances to determine follow-up decisions in disturbances. CNN is one of the advanced versions of supervised machine learning algorithms that are quite powerful in extracting information from images. Hence, an image is constructed into a matrix dataset and then processed to retrieve some patterns through mathematical computations. CNN is already widely used for computer vision or other applications that require visual analysis. In this research, the benefit of CNN is applied to obtain a disturbance-type classification based on the images generated by DFR.

CNN is the result of combining Convolutional operations with the backpropagation algorithm [18]. A CNN model consists of an input layer, Convolutional layers, pooling layers, fully connected layers, and an output layer. The Convolutional layers comprise multiple 2-D feature maps, while the fully connected layers comprise several independent neurons [19]. In this study, the CNN model uses an input denoted as x , with an output y_1 representing the result of the classification.

$$X_0^l = f\left(\sum_{i \in m} X_0^{l-1} K_{i_0}^l + B^l\right) \tag{7}$$

where:
X_0^l : The output at layer l for the position or node 0.
f : The activation function applied after the Convolutional and bias addition.
m : Set of neighbors (in the case of a graph) or a local region (in CNNs).
$K_{i_0}^l$: The kernel (or weight) at layer l between position i and 0.
B^l : The bias term for layer l, added after the weighted summation.

3. Results and Discussions

3.1 DFR Data

The data used to develop the CNN-based fault signature analysis model consists of 600 images divided into six classifications with 100 images per class, as presented in Table 1. Examples of the DFR image data are provided in Figure 2 - Figure 7. It can be seen that the waveform during disturbance in the DFR images has altered from the normal condition. Based on field conditions, normal conditions can be seen from the absence of impulsive changes in current and voltage increases. For other objects, there is a fairly constant sinusoidal increase with a medium period of time. While lightning conditions, seen from the presence of a voltage drop that experiences a decrease in the peak sinusoidal phase with a short period of disturbance. Then for trees, there is a phase of a tiered current increase with a medium length of time. Almost similar to trees, for animals there is an indication of a tiered current increase with a short time. And finally for equipment breakdowns there is an indication of a very unstable sinusoidal current with a fairly short time.

The data is divided into two major datasets: the training and testing datasets. The training dataset consists of about 500 data, with a small variation for each class. The training dataset is also separated for cross-validation. Meanwhile, the test dataset with around 100 of the total data is used to confirm the accuracy of the proposed model.

Table 1. Classification of disturbance type

Variable	Description	Value
0	No System Fault	True (1), False (0)
1	Lightning/Flash Isolator	True (1), False (0)
2	Metal Object/ Kites	True (1), False (0)
3	Breakdown/Broken Conductor	True (1), False (0)
4	Animal	True (1), False (0)
5	Tree	True (1), False (0)

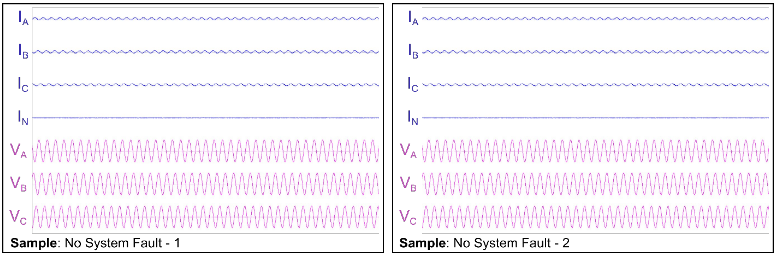

Figure 2. Image data example for “no system fault”

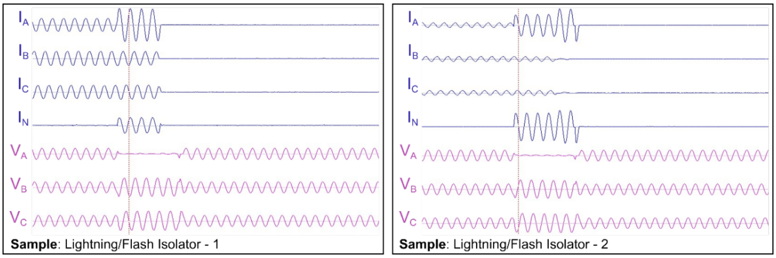

Figure 3. Image data example for “Lightning/Flash Isolator”

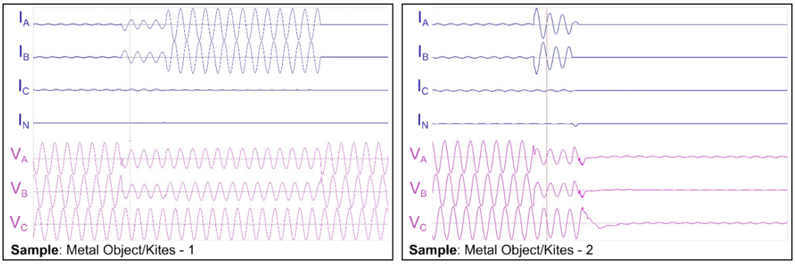

Figure 4. Image data example for "Metal Object/ Kites"

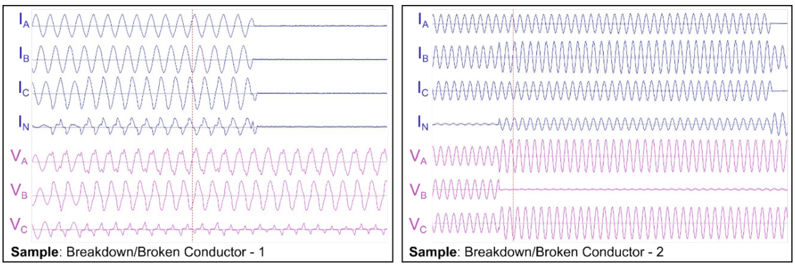

Figure 5. Image data example for "Breakdown/Broken Conductor"

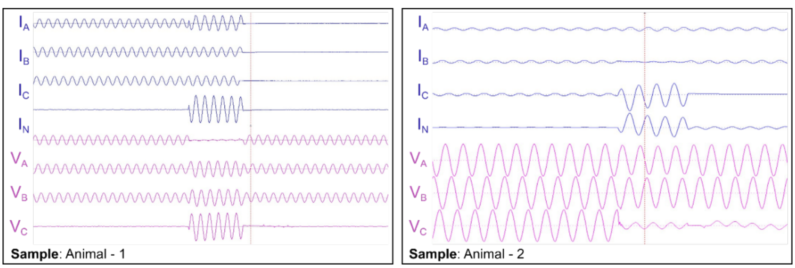

Figure 6. Image data example for "Animal"

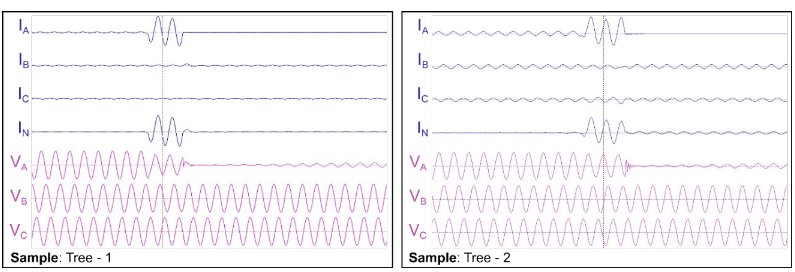

Figure 7. Image data example for "Tree"

3.2 CNN Model Development

In the CNN method used to analyze fault signatures in the transmission system, the VGG19 architecture is employed. VGG19 consists of 19 layers, including Convolutional, pooling, and fully connected layers, and utilizes uniform 3×3 filters across all Convolutional layers to effectively capture local spatial features. This study used a fine-tuning process to implement the VGG model and obtain the best results. The VGG architecture offers several strengths that make it suitable for fault diagnosis in power transmission systems, especially when fault signals are transformed into visual formats such as wavelet spectrograms or time-frequency images. Its structure is based on a consistent and straightforward design, using only 3×3 Convolutional layers and 2×2 max-pooling layers, which makes it effective in learning local features from images. This is especially beneficial for identifying transient patterns or sudden changes commonly found in electrical fault signatures. With deeper versions like VGG-16 or VGG-19, the model can extract hierarchical features, allowing it to accurately distinguish between various types of faults such as single line-to-ground (L-G), line-to-line (L-L), double line-to-ground (L-L-G), and three-phase faults.

One of VGG's key advantages is its compatibility with transfer learning. Since fault data in power systems is often limited, VGG models pretrained on large datasets like ImageNet can be fine-tuned on specific fault datasets, resulting in high classification accuracy even with relatively small amounts of data. Compared to more complex architectures like GoogLeNet or ResNet, VGG is also more stable and easier to train, making it a practical choice for engineers and researchers who want effective results without deep architectural complexity. Its widespread support in frameworks like TensorFlow and PyTorch makes implementation straightforward, which is valuable for academic research and industrial applications.

The ReLU activation function is applied after each Convolutional layer to introduce non-linearity, while max-pooling layers are used for dimensionality reduction. The input to the VGG19 model is resized to match the required dimensions, and the architecture is selected for its proven performance in feature extraction and classification tasks, especially in scenarios involving structured patterns such as fault signatures.

Based on the training results, three types of curves were obtained related to the accuracy validity of the Convolutional Neural Network in analyzing fault signatures. In the first curve, as shown in Figure 8, the accuracy and loss curves during the training process intersect. The accuracy curve increases and approaches 1, while the loss curve decreases and approaches 0. This indicates that the model's accuracy improves, and the training loss decreases progressively, demonstrating effective learning during the training phase.

The second curve in Figure 9 compares the accuracy of the data for training and the data for testing using the Convolutional Neural Network method. The curve shows that the accuracy of both test and training data increases until it approaches the value of 1. This is a good indication that the learning conditions on the Convolutional Neural Network system have increasing accuracy.

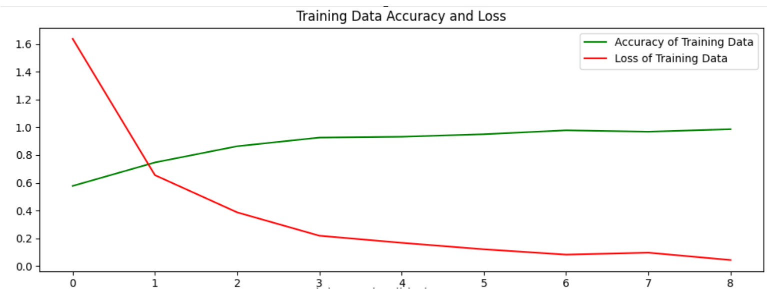

Figure 8. Comparison of Changes in Accuracy and Loss Results Graphs of CNN Training Data

Figure 9. Comparison of Changes in Accuracy Results Graph of Training Data and Test Data in CNN

Meanwhile, the third curve in Figure 10 compares the loss between training data and testing data using the Convolutional Neural Network method. The curve for both datasets shows a downward trend, approaching a value near zero, which indicates that the loss level in the Convolutional Neural Network-based analysis is steadily decreasing. This trend suggests that the model is generalizing well and is not overfitting to the training data.

Figure 10. Comparison of Changes in Error Results Graph of Training Data and Test Data in CNN

3.3 Fault Signature Prediction Results

This experiment also obtained a Confusion Matrix, as shown in Figure 11. The main diagonal of the Confusion Matrix, which represents the number of correct predictions made by the model, contains significantly more value than the off-diagonal elements. This indicates that the CNN model demonstrates high accuracy in its predictions.

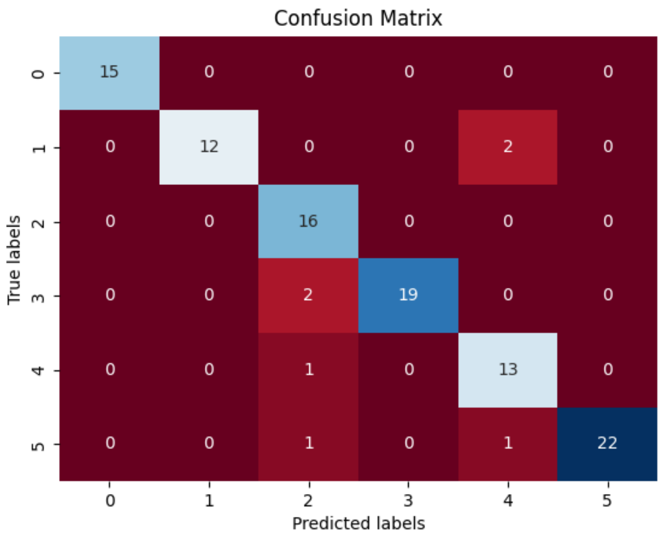

Figure 11. Obtained Confusion Matrix

The classification conditions were mapped from the testing data results, as shown in Figure 12. In this condition, the accuracy and correctness level of the Convolutional Neural Network analysis on fault signatures were captured.

The results demonstrate the model's ability to identify and classify fault types correctly, validating the effectiveness of the Convolutional Neural Network approach in recognizing fault signature patterns.

```
Epoch 9: early stopping
2025-01-01 09:43:49.947342: I tensorflow/core/framework/local_rendezvous
4/4 ━━━━━━━━━━━━━━━━━━━━ 15s 4s/step
accuracy is: 93.55%
4/4 ━━━━━━━━━━━━━━━━━━━━ 15s 3s/step - accuracy: 0.9523 - loss: 0.2979
Accuracy: 93.54838728904724 %
```

Figure 12. Accuracy Result from Pyton

Based on the evaluation and testing results of the CNN system using VGG19 for fault signature analysis, the achieved final system accuracy was 93.87% with a loss of 6.13%. This result indicates that the proposed model can accurately identify fault types with a high degree of reliability, demonstrating its potential for practical implementation in power system fault diagnosis.

The model's accuracy can be further evaluated based on each type of disturbance, as presented in Table 2. The examples of the results of fault signature prediction using the CNN model are shown in Figure 13 – Figure 18. These results show that the proposed model can distinguish and classify the DFR images into appropriate classes.

Table 2. Accuracy for each type of disturbance

Class	Description	Accuracy
0	No System Fault	1
1	Lightning/Flash Isolator	0.82
2	Metal Object/ Kites	1
3	Breakdown/Broken Conductor	0.94
4	Animal	0.87
5	Tree	1

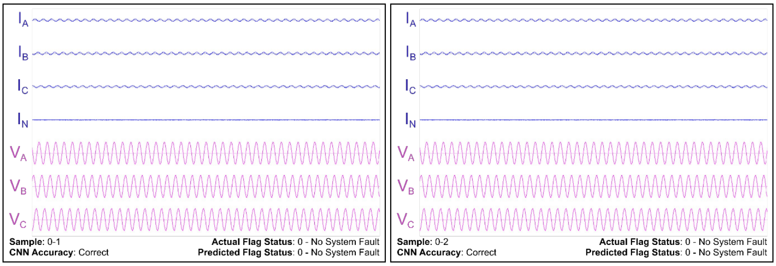

Figure 13. Prediction result example for "no system fault"

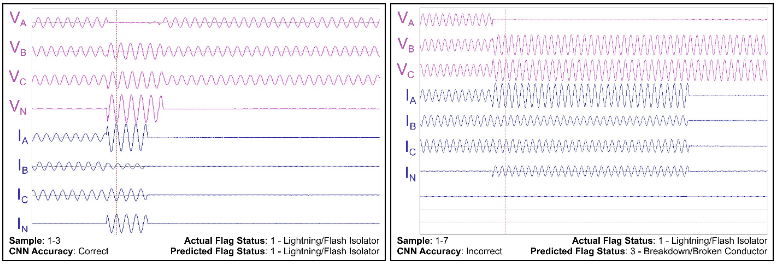

Figure 14. Prediction result example for "Lightning/Flash Isolator"

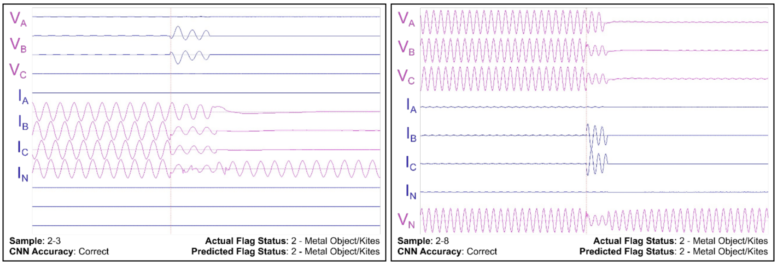

Figure 15. Prediction result example for "Metal Object/ Kites"

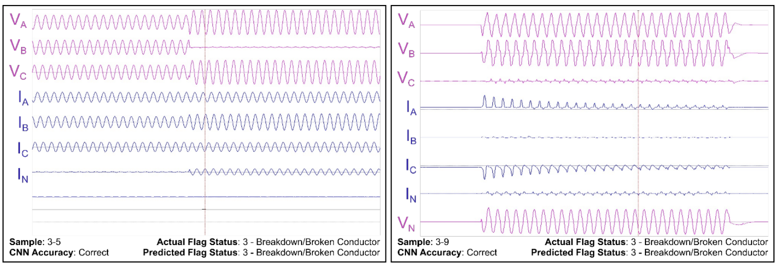

Figure 16. Prediction result example for "Breakdown/Broken Conductor"

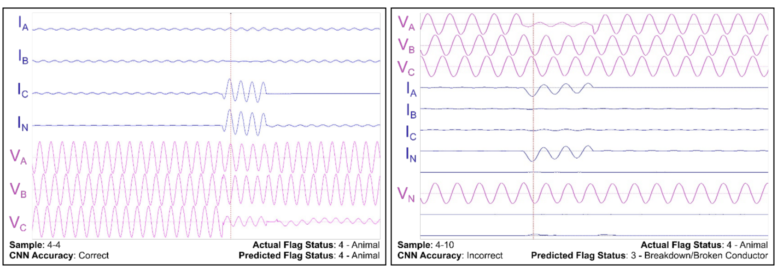

Figure 17. Prediction result example for "Animal"

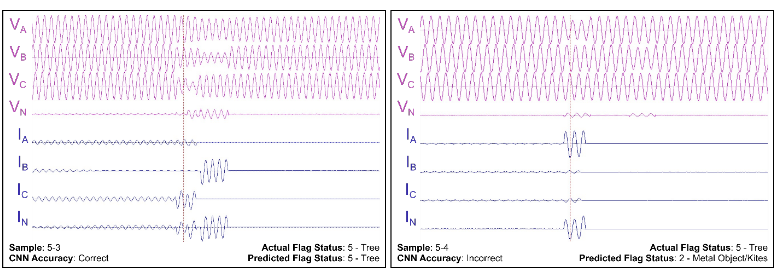

Figure 18. Prediction result example for "Tree"

4. Conclusion

Based on the Confusion Matrix results, the classification condition as "No System Fault" had 15 data correctly classified. In the" Lightning/Flash Isolator" classification condition, 12 data were correctly classified, and two were incorrect as "Animal". The "Metal Object/ Kites" classification condition had 16 data correctly classified. While in the classification condition as "Breakdown/Broken Conductor," 19 data were correctly classified, 2 data incorrect as "Metal Object/ Kites". In the classification condition as "Animal", there were 13 data correctly classified, 1 data incorrectly classified as "Metal Object/ Kites", and finally, classification condition as "Tree" had 22 data correctly classified, 1 data incorrect as "Metal Object/ Kites" and 1 data incorrect as "Animal". From these conditions, it was found that almost all data were on the diagonal line, which means that the conditions were mostly in accordance with predictions.

Using a Convolutional Neural Network (CNN) for fault signature analysis in transmission system disturbances yielded satisfactory results, achieving an accuracy of 93.87%. This performance was obtained using a dataset of 100 samples for testing and 500 datasets for training, with six classification categories. The accuracy can be further improved by reducing the number of classification categories or by increasing the dataset size with high-quality data. In particular, expanding the dataset would significantly enhance the model's ability to generalize and recognize patterns more effectively, thereby improving overall classification performance.

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