Diagnosis of Partial Discharge in Power Transformer using Convolutional Neural Network

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Abstract

In an electric power system, power transformers are essential. Transformer failures can degrade the quality of the power and create power outages. Partial Discharges (PD) are a condition that, if not adequately monitored, can cause power transformer failures. This project addresses the diagnosis of PD in power transformer using the Phase Amplitude (PA) response of PRPD (Phase-Resolved Partial Discharge) patterns recorded using PD Detectors. It is a widely used pattern for analysing Partial Discharge. A Convolutional Neural Network (CNN) is used to classify the type of PD defects. The PRPD patterns of 240 PA sample images have been taken from power transformer of rating 132/11 KV and 132/25 KV for training and testing the network. The feature extraction has also been done using CNN. In this work, the classification of PD faults is done using a supervised machine learning technique. The three different classes of PD faults such as Floating PD, Surface PD and Void PD are considered and predicted using Support Vector Machine (SVM) classifier. Simulation study is carried out using MATLAB. Based on the results obtained, it is found that CNN model has achieved a greater classification accuracy and thereby the life span of power transformer is enhanced.

Keywords: Power Transformer, Partial Discharge, Support Vector Machine, Convolutional Neural Network

1. Introduction

Power transformers are the most important component of any power system. Effective fault identification is essential for avoiding costly outages of electrical network systems. The power transformer being the principal source for changing voltage and in the transmission

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and dispensing network, one of the most crucial components in sustaining stable operational conditions of a power system plays an inevitable role.. This may cause insulation degradation over time due to slow erosion in the winding, resulting in PD. Furthermore, if PD problems are not detected early on, the transformer insulation may degrade. Partial discharge measurements and analysis are routinely used in power transformers as a diagnostic indicator of insulation damage. PD, which is described as a localized dielectric breakdown of a small area of a solid or liquid electrical insulation system causes high voltage stress, which might result in total insulation failure. However, due to electromagnetic noise in the substations, measuring and analysing PD is challenging because of its great sensitivity and noise resistance, the Ultra High Frequency (UHF) sensor method is commonly utilised for PD diagnosis[1]. The ability to recognise UHF signals can be particularly useful in assessing the internal condition of a device, allowing not only to identify defects but also to understand what kind of faults they are, where they are, and how dangerous they are. UHF sensor method has showed promising results in PD classification and recognition among the various detection approaches[2].

Machine learning methods such as Artificial Neural Networks, Support Vector Machines and decision trees has offered as viable techniques for a transformer defect diagnosis due to the recent and rapid evolution of technology. The feature extraction of the Phase Amplitude sample images was done based on an SVM for the classification task. In recent years, CNN the most widely used deep learning architecture have gained prevailing success. Layers from the input to the output, CNN is divided into various learning stages consisting of a multiple layersin the centre, such as convolution layers, pooling layers, a dropout, and completely connected layers [1]. Each layer has a set of filters, kernels, or neurons that address combinations of inputs from previous layers. The main goal of this research is to create a CNN model that meets the critical requirements for power transformer PD fault classification [6].

In this work, the CNN model is made up of convolutional layers and max-pooling layers, and its main goal is to extract features from the PRPD signal. Overfitting is avoided by the use of dropout and batch normalisation.

2. An Overview of Partial Discharge in Power Transformers

PD is caused by an electrical breakdown in the insulation that does not fully bridge the electrodes, which is a localized electric stress. This mechanism produces delayed insulation deterioration, shortening the power transformer's insulating life When the electric field reaches a certain level, it is said to have crossed the threshold, PD occurs, causing the surrounding medium to partially disintegrate [8]. Pulsing currents with durations ranging from nanoseconds to microseconds are part of the PD's transient activity. PD happens when the voltage stress within the cavity surpasses the inception voltage.

PD can be caused by a variety of defects in the oil-paper insulation of power transformers [3]. The defects are gaps caused by the separation of layers of paper surrounding the windings in the absence of oil impregnation [12].According to the natural aging of metal tanks and moving metallic particles in the insulating oil and environmental factors such as humidity and surge voltage, voids occur in the bushings and also due to age, contaminants in the oil and retained moisture, gas bubbles develop in the insulating oil. Moisture was trapped in solid insulation during the production process and tracking in solid insulation [5].The beginning of PD is caused by a localized static electric charge caused by oil flow and an increase in the electric field.

2.1 PRPD Measurement Patterns

Power transformer PD diagnostic is a useful technique for classifying various faults. The main purpose of PD diagnosis is to determine where the PD is coming from in the insulation and to differentiate between different types of faults. A PRPD pattern is a visual depiction of partial discharge (PD) activity in the context of an AC cycle's 360 degrees [11].

PRPD stands for PD pulse phase angle, discharge voltage amplitude, and number of pulses, where q and n are the PD pulse phase angle, discharge voltage amplitude, and number of pulses, respectively. The amplitude of each discharge event (y-axis) is shown against their phase angle in the PRPD graphic (x-axis) [7]. The amplitude is measured in dBmV with a Transient Earth Voltage sensor in this case, and 10 seconds of activity is exhibited in relation to the 50Hz system frequency. The voltage supplied across each flaw rises and falls in lockstep with the primary voltage on a power system, forcing the defect to discharge exclusively at certain periods and amplitudes.

3. Classification of Partial Discharge with CNN

In this study, the PD in power transformer is diagnosed using the CNN model with SVM classifier. The three different types of PD defects are classified with greater accuracy.

3.1 Convolutional Neural Network and Its Application

CNN are based on the visual cortex of the brain, but they can be employed for signal processing and identification in addition to visual perception. Every filter, also called as a Kernel, is superposed in sequential spots along the image and produces a characteristics map through convolutional networks in the convolutional layer. Convolutional layers are the first layer to extract information from an input picture and are the most important building blocks of CNN. It makes a single value out of all the pixels in its receptive area. It reduces the picture size by combining all of the data in the field into a single pixel. Pooling (down-sampling) layer reduces computational strain by lowering the amount of feature maps while simultaneously introducing positional invariance [4]. There are two forms of pooling that are commonly used maximum and average. The maximum value of each local cluster of neurons in the feature map is used in max pooling, whereas the average value is used in average pooling. The fully connected layer generates a prediction using the previously flattened Convolutional features obtained by the preceding Convolutional layer.

3.2 AlexNet Architecture

Alexnet was the the first joining the network to improve speed by using a graphics processing unit (GPU). Alexnet architecture consists of five convolutional layers, 3 max-pooling layers, 2 normalization layers, 2 fully connected layers, and 1 softmax layer. Max pooling is done using the pooling layers. Due to the presence of completely linked layers, the input size is fixed as 224x224x3, however owing to padding it's actually 227x227x3. Alexnet contains 60 million parameters in all.

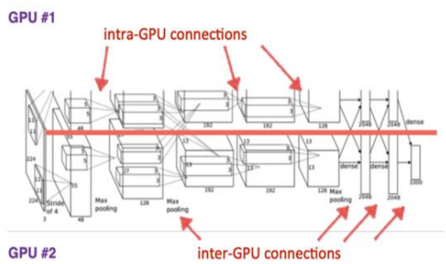

Figure 1. Alexnet architecture

3.3 Implementation of PD Diagnosis using CNN

Figure 2 depicts the architecture of CNN for categorizing PRPDs in power transformers. The model structure of CNN model consists of an input layer, convolutional layers, max-pooling, dropout, batch normalization, flattens, fully connected layers, and an output layer.

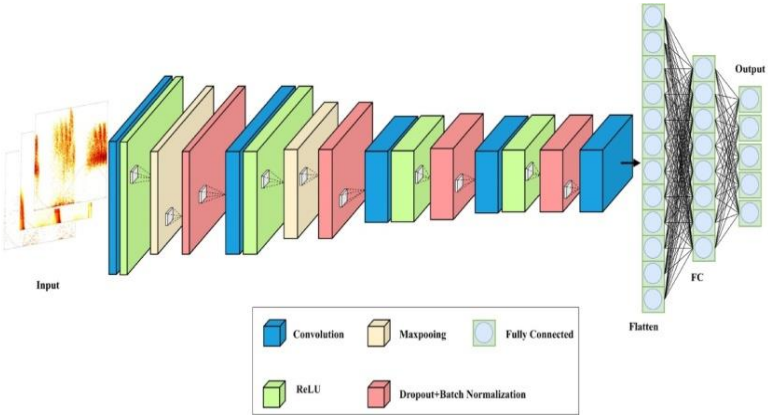

Figure 2. CNN Architecture for fault classification

Table 1. Detailed structure of the CNN model

Type of Layer	Kernel Size	Output Size	Padding
Conv + Relu	4*4	55*55*96	[0 0 0 0]
Batch norm	-	55*55*96	-
Max Pooling	2*2	27*27*96	[0 0 0 0]
Conv + Relu	1*1	27*27*256	[2 2 2 2]
Batch norm	-	27*27*256	-
Max Pooling	2*2	13*13*256	[0 0 0 0]
Conv + Relu	1*1	13*13*384	[1 1 1 1]
Max pooling	2*2	6*6*256	[0 0 0 0]
Dropout	0.5	1*1*3096	-
Fully Connected layer	-	1*1*1000	-

Table 1 shows the CNN model's complete structure. The overall parameter in the training set is 240.

Similarly, batch normalisation, a common and successful strategy for routinely speeding up network convergence, was utilised to minimise disappearing and ballooning gradients induced by internal covariance shifts during training [9].The completely connected layer follows the classification layer often known as a softmax layer. As shown in Table 1, the layer's output value was set to be the same as the number of objects to be classified.

4. Feature Extraction Using Deep Learning Network

Feature extraction is the process of converting raw data into numerical features that may be processed while maintaining the data from the original data set. It yields better results than simply implementing machine learning to raw data. The extraction of features can be done manually or automatically. These characteristics are simple to use while still accurately and uniquely describing the real data set. Feature extraction aids in the reduction of unnecessary data in a data collection. Finally, minimizing the data makes things simpler for the machine to create the network with much less effort, as well as accelerating the machine learning and generalization processes.

4.1 Support Vector Machine

SVMs, called as support-vector machine are supervised learning models that evaluate data for classification analysis in machine learning. SVMs, which are based on statistical learning frameworks, are one of the most reliable prediction approaches. SVMs may also be used for image classification. After only three to four rounds of relevant feedback, SVMs achieve much greater accuracy than standard query refinement systems. This holds true for picture segmentation software as well.

4.2 Confusion Matrix

A confusion matrix is a table that summarizes the results of classification problem prediction. The entire number of correct and incorrect predictions is added together and divided by category using count values. A confusion matrix (also known as an error matrix) is a numerical method of describing the efficiency of visual classification. As each class has an unequal amount of variables or the information has more than two classes, classification performance alone may be deceptive [10]. The event row is labeled "positive," whereas the no-event row is labeled "negative." The event column of forecasts is set to "true," whereas the no-event column is set to "false."

5. Results and Discussion

As a result, PD measurements are a crucial diagnostic tool for monitoring a power transformer's insulating state. PD can occur in solids, gases, and liquids. Furthermore, partial discharge voltage is affected by the insulation material. In this work, three types of PD defects such as Floating PD, Surface PD and Void PD are classified using CNN model in MATLAB. For the above PD defects, 240 PA sample images were taken from PRPD measurements of two different power transformers. Out of 240 PA samples, 126 PA sample images were taken from surface PD, 40 samples for floating PD and 74 for void PD.

The PA sample images are given as input to the CNN for training and testing. Majority of the PA sample images 192 (over 80%) were trained and balance 48 (over 20%) were tested. Using Alexnet architecture, 25-layer models has been formed in Deep Network Designer toolbox. The feature extraction has been done for extracting the CNN model from training and testing datasets.

The Series Network or DAG Network object net is analyzed in the training phase using the Deep Learning Network Analyzer tools. The function gives extensive information about the network layers as well as an interactive depiction of the network architecture. With algorithms, pre-trained models and applications Deep Learning Designer Toolbox provides a platform for developing and executing deep neural networks. The network architectures may be developed using the Deep Network Designer tools to build, evaluate, and train networks visually.

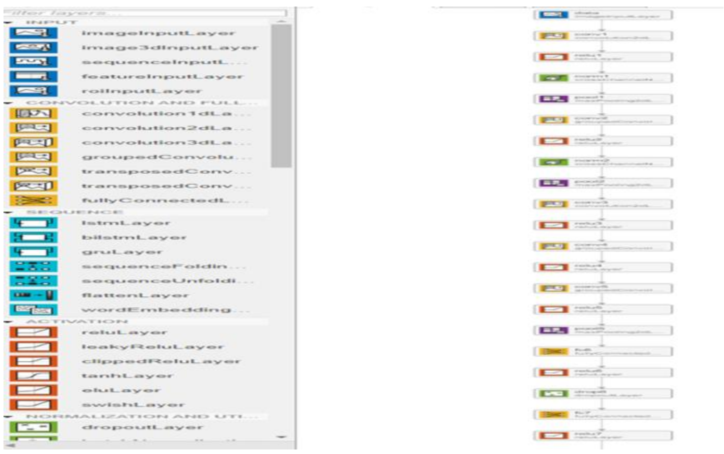

Figure 3. Alexnet architecture for PD defect classification

Figure 3 shows the formation of 25 - layer Alexnet architecture model in Deep Network Designer toolbox. Filters with convolutions and a nonlinear activation function

ReLU are used in each convolutional layer. Max pooling is done using the pooling layers. Due to the presence of completely linked layers the input size is fixed. The goal of feature extraction is to minimise the amount of features in a dataset by producing new ones from the old ones and then rejecting the old ones. The original set of features should then be able to summarise the majority of the information in the new reduced set of features. Feature extraction in image processing starts with a collection of measured data and constructs derived values that are meant to be useful and non-redundant, easing the learning and generalisation processes and in some situations leading to superior human interpretations. Dimensionality reduction is linked to feature extraction.

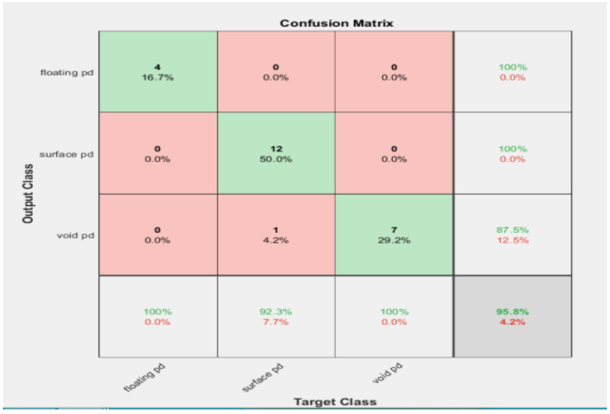

Figure 4. Confusion matrix for PD fault classification

A confusion matrix is a table that visualizes and summarizes the performance of a classification algorithm. All the diagonal elements represent results that have been appropriately categorized. On the off-diagonal lines of the confusion matrix, the incorrectly classified outcomes are shown. As a result, the best classifier will also have a confusion matrix with only diagonal elements and zero values for the rest of the elements. After the categorization procedure, a confusion matrix yields actual and expected values. Figure 5.2 clearly shows that the Floating PD and Surface PD defects are correctly diagnosed with 100% accuracy whereas void PD defects has been classified with 87.5%. Thus, the three different types of power transformer PD detector classified with a overall classification performance accuracy of 95.8%.

6. Conclusion

In this work, the diagnosis of PD in the power transformer using CNN model has been classified. The Phase – Amplitude response of PRPD pattern sample images are taken from two different power transformers for validating the proposal. The six types of PD defects in power transformer are protruding electrode PD, particle PD, floating PD, surface PD, turn to turn PD and void PD. Among these, the three major types of PD defects such as floating PD, surface PD, and void PD are considered. In this work, SVM is used to classify three types of PD defects using MATLAB. Floating PD and surface PD has achieved a fault classification performance of almost 100% accuracy, whereas void PD are classified with 87.5% accuracy. Based on the results obtained, it is found that CNN model has achieved a higher classification accuracy of 95.8% and only 4.2% of PA samples are misclassified and provides a comprehensive solution for diagnosing PD faults in prospective field applications and servicing. Thus, the lifespan of power transformer is enhanced by using CNN model.

References

[1] The-duongdo, etal,"Convolutional-Neural-Network-Based Partial Discharge Diagnosis for Power Transformer Using UHF Sensor", IEEE Access,2020.

[2] MD Rashid Hussain,etal,"Overview and Partial Discharge Analysis of Power Transformers", IEEE Access,2021

[3] K.Firuzi,etal,"Partial Discharges Pattern Recognition of Transformer Defect Model by LBP & HOG Features", IEEE Access,2018.

[4] Sonia Barrios, etal, "Partial Discharge Classification Using Deep Learning Methods—Survey of Recent Progress",MDPI, 2019.

[5] Jun Jiang,et al, "Partial Discharge Detection and Diagnosis of Transformer Bushing Based on UHF Method", IEEE Sensors, DOI:10.1109/ JSEN. 2021.3066809,Volume:21,Issue:15,2021.

[6] Suganya Govindarajan, et al, "Partial Discharge Location Identification Using Permutation Entropy Based Instantaneous Energy Features", IEEE Transactions on Instrumentation and Measurement, DOI:10.1109/ TIM.2021.3121477, (Volume:70),2021.

[7] "Partial Discharges In Transformers",CIGRE,February,2017.

[8] Rui Zhang, etal, "Bubbles in Transformer Oil: Dynamic Behaviour, Internal Discharge, and Triggered Liquid Breakdown", IEEE Transactions on Dielectrics and Electrical Insulation, Volume: 29, Issue: 1,2022.

[9] Suganya Govindarajan,etal, "Partial Discharge Location Identification Using Permutation Entropy Based Instantaneous Energy Features", IEEE Transactions on Instrumentation and Measurement, Volume: 70,2021.

[10] ShengyaSun,etal, “Partial Discharge Pattern Recognition of Transformers Based on the Gray-Level Co-Occurrence Matrix of Optimal Parameters”, IEEE Access, Volume: 9,2021.

[11] TohidShahsavarian,etal, “A Review of Knowledge-Based Defect Identification via PRPD Patterns in High Voltage Apparatus”, IEEE Access, Volume: 9,2021

[12] Shigeyoshi,etal, “Characteristics of Creepage Discharge in Oil/Pressboard Composite Insulation”, IEEE Transactions on Dielectrics and Electrical Insulation, Volume: 28, Issue: 2,2021.