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Comparative Evaluation of Deep Learning CNN Techniques for Power Quality Disturbance Classification

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Abstract

For the power system to be stable and reliable, power quality disturbances (PQDs) must be classified. In this work, deep learning was implemented for the purpose of categorizing PQDs. The transfer learning techniques such as ResNet-50, AlexNet, and GoogLeNet were compared and evaluated for the suitability of classifying PQD signals. Accuracy, classification probability, and explainability through GradCAM- an explainable AI technique was evaluated as a grading reference for the comparative analysis. Examination of the three criteria revealed ResNet-50 as the best among all the three architectures for classifying PQD signals since depending on the accuracy.

Keywords: *GradCAM, Deep Learning, Power Quality Disturbances, Recurrence plot, Transfer Learning.*

I. Introduction

The integration of renewable energy sources to expand power networks is a challenging task. Since renewable energy sources are unpredictable, their energy output is non-dispatchable, intermittent, and subject to significant variations[1]. Such large oscillations due to the increasing usage of renewable energy sources pose fundamental questions about the quality of power. In presence of power quality interruptions such as voltage sag, voltage swell, harmonics, transients, interruption, flicker, notch, etc., the quality of the electric power deteriorates. These interruptions cause end-user equipment to malfunction which causes a large financial loss. To improve power quality, it is thus crucial to identify PQ disturbances as a foremost step toward building a reliable network[2].

In[3], non-linear disturbances are categorized using a variational mode decomposition approach, in which a band of the signal is formed as a consequence of decomposition into some mode function. A Stockwell transform along with a Time-Time transform was implemented for signal synthesis and features were selected using NSGA-II(non-dominated sorting algorithm) in[4]. An innovative version of wavelet transform known as tunable Q-wavelet transform was introduced in[6] for PQD signal conditioning and classified using support vector machines. In[7] features were extracted from S-transform and Wavelet transform classified. A unique deep convolutional neural network-based full-closed-loop method for identifying and categorizing power quality issues are described in[8]. An ant colony optimization model for the same is presented in[9]. The aforementioned procedures are efficient, but owing to the need for the acquisition of some obvious features, they are challenging to master, and training the model from scratch requires a lot more time and complexity. As a result, the approach of transfer learning may be employed for categorization.

This article compares and evaluates the appropriateness of three deep-learning CNN architectures for categorizing

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power quality issues. The power quality disturbances were converted into image-based data using a recurrence plot and then sent to GoogLeNet, ResNet-50, and AlexNet. Using explainable AI-gradCam, an attempt was made to demonstrate categorization concepts on the operation of deep learning black boxes.

2.0 Database Preparation

The various classes described in this work are sourced from the database shown in[10]. Signals are generated as per the IEEE standard 1159-1995[11]. Table 1 represents all 9 classes of power quality signals and disturbances based on their class type (single, double). Depending on the situation, some characteristics, such as sampling frequency, sample generation number, and fundamental frequency of the signals, can be modelled. In order to create the power quality signals, 100 data per class of fundamental frequency signals at 50 Hz were taken at a rate of 2 kHz. The signals generated were converted from time series to data to image data through a concept Recurrence plot[12]. The Grayscale images were converted into RGB for fulfilling the input layer of CNN architectures.

Table 1: Power quality disturbances signal

Class	Class name	Brief description
I	Sine	Fundamental waveform
II	Sag	Voltage reduced to 20% of nominal voltage
III	Swell	Increase in nominal voltage up to 1.1-1.8 p.u.
IV	Interruption	Supply voltage/load current returns to 0.1 p.u. for a moment<60 secs.
V	Impulse	Steady-state condition of voltage affected by non-power frequency change
VI	Oscillatory Transients	An instantaneous change in polarity of the voltage/current.
VII	Harmonics	Integer multiples of fundamental frequencies.
VIII	Flicker	Rapid variations in voltage waveform.
IX	Notch	Periodic disturbances in voltage due to switching operation.

3.0 Conceptual Background

This section includes a brief discussion of how the architecture used in the article can be modelled.

A. CNN-Convolutional Neural Network

In computer vision, CNN is a powerful deep-learning technique that is frequently used for image categorization. The core elements of CNN are as explained below:

Convolutional layer: The input image is processed using a number of filter banks, also known as kernels, in the convolution layer. In the forward paths, the filters are transversely convolved with the input image's height and width separately. It returns a two-dimensional (2D) feature map. The rectified linear unit layer, which follows the convolution layer, raises the network nonlinearity via a rectified function[9].

Pooling layer: This layer decreases the feature map's dimension while retaining the important data that was recovered by the convolution layer. The case of over-fitting data is controlled by a variety of operators and downsizes the sampling.

Fully connected layer: In the ultimate layer score is provided according to the weights assigned from the pooling layer. By transforming the 2D feature maps into a 1D feature vector, it feeds forward the network and determines scores for each category. The trained model is used by the Softmax layer to forecast the likely class of the test data after converting the scores into probabilities.

B. AlexNet CNN

AlexNet architecture developed by Alex Krizhevesky et al.[13], consists of eight layers, five of which are convolutional, two are fully connected (fc6, fc7), and one is softmax.. AlexNet input picture is 227×227 pixels in size. Fig.1 depicts the AlexNet CNN organizational structure. The first and second convolutional layers, respectively, employ 96 and 256 kernels of sizes 11×11×3 and 5×5×48. A max pooling layer with 3×3 filters follows each convolution layer. The third and fourth convolution layers use 384 filters each, and the fifth one uses 256. Next is max pool layer of kernel size 3×3 and then the softmax layer can classify up to 1000 class labels, receives the high-dimensional feature vector from the fully linked layer.

C. ResNet-50 CNN

In[14], ResNet, or Residual Network, was introduced, which was 50 layers deep, and a vanishing gradient issue was solved by enabling an additional short-cut conduit for the gradient to flow through. ResNet's skip connections address the issue of disappearing gradients in deep neural networks. The identity functions that the model learns from these linkages assure that the upper layer will perform at least as well as the lower layer, if not better.

D. GoogLeNet CNN

There are 22 layers in the architecture overall. The architecture was created with consideration for computational effectiveness. the concept that even with limited processing resources, the architecture may be used on individual devices[15]. Two more classifier layers are included in the design and are coupled to the output of the Inception (4a) and Inception (4d) layers. The classifiers' architectural specifics include a typical pooling layer with a 5×5 filter and a stride 3, for dimension reduction and ReLU activation, a1–1 convolution with 128 filters is used, layer with 1025 outputs, and ReLU activation that is fully connected. A 1000-class softmax classifier produces results comparable to the primary softmax classifier.

E. Transfer Learning CNN

The amount of time to train a network from the beginning is a significant problem for CNN. The pre-trained models' weights are added to the current model in transfer learning Only the classification layer and the final few hidden levels of the CNN network are replaced with new layers that have distinct weights and learning rates. This trains the network for the current task rather than training it entirely starts with random weights. The network's training time is significantly cut down through this process, making the network computationally faster and functioning reasonably well.

4.0 Visualization of CNN Architectures

Despite the algorithms' apparent effectiveness, there is a problem with them since they are inherently difficult to understand because deep learning algorithms are frequently highly complicated. The conclusions and suggestions produced by the algorithms in Section III may therefore be difficult for professionals in the field of power systems to trust, which reduces their actual utility. This challenge is particularly evident in situations requiring a high degree of dependability, which is frequent in the energy sector. This section deals with reason of the decision-making of the algorithms.

GradCAM is a method for visualizing the model's concentration that has been extensively researched in the area of classification in two dimensions. It creates a rough localization map emphasizing the key areas in the image for prediction with the aid of gradients of any target theme flowing into the final classification layer. In this article, we employ the GradCAM approach[16], which enables visualization of the input areas crucial to these models' predictions, thereby increasing the transparency of CNN-based models. Using the gradient data feeding into the last convolution layer of the CNN, GradCAM calculates each neuron's relevance for a significant decision.

5.0 Results and Discussion

In the current work, a total of 1350 data images were taken, with 100 images in each class. The split ratio of the obtained pictures for training and testing was 70:30. Thus, 945 images altogether were used to train the architecture, and 405 images were used for testing. In the model, the newly created, completely linked layers were trained. The learning rate was maintained at 0.001. The number of epochs in this work is limited to 20, and 580 iterations were carried out for training, yielding an average of 29 iterations per epoch. Each architecture was evaluated at the fixed metric such as epoch and learning rate for accurately classifying PQD signals. In Table 2, deep learning classification results can be observed where the maximum accuracy is 96% belonging to ResNet-50 architecture.

Table 2: Accuracy comparison of architectures

Accuracy (in %)		
AlexNet	GoogLeNet	ResNet -50
88	93	96

A. Performance Evaluation of CNN Architectures

For validating the potency of the architecture on the ground of accuracy, a random signal belonging to each class was generated. The chosen signal was neither the part of training dataset nor the testing dataset. Table 3 displays the architecture's outcomes after being subjected to random signals. The purpose was to observe the behaviour of each architecture concerning a given input. ResNet-50 showed 100% accuracy in predicting all the validation images precisely, whereas AlexNet predicted impulse signal image as sine signal image and GoogLeNet predicted impulse as sine and oscillatory signal as impulse signal. Thus, it can be concluded that the ResNet performed best among all the other techniques based on the classification of random images fed to the architecture.

B. GradCAM Explainability of CNN Architectures

A system that uses artificial intelligence (AI) to assist power quality experts should be somewhat explicable and should let the human expert review the possibilities and exercise judgment. Illustration in Fig.1 is carried out by utilizing the concept of GradCAM – an explainable Artificial Intelligence method. The classification result is passed to Grad-CAM, which generates maps for each predicted score.

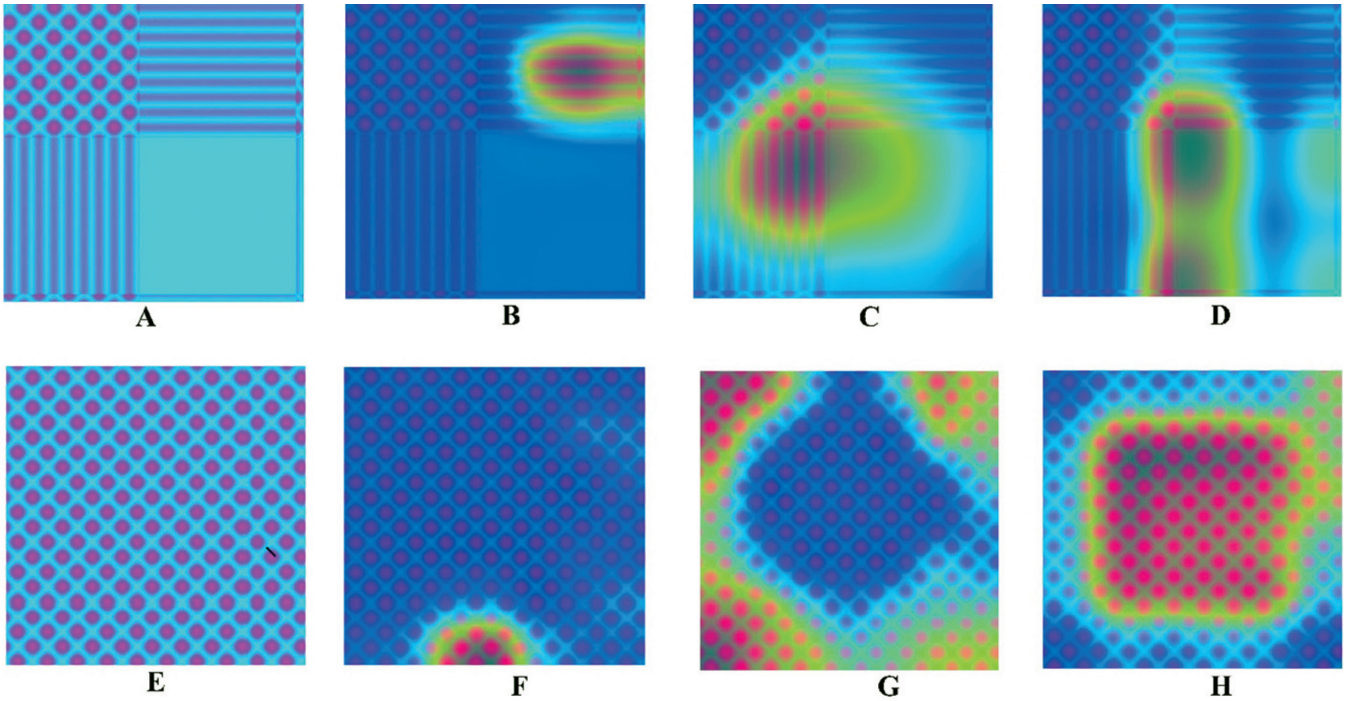

Fig.1: (A) is the RP image of interruption signal. (B), (C), (D) are the gradCAM enhanced features of the image on the basis of which ResNet-50, AlexNet and GoogLeNet predicted the class of the image (A) respectively. (E) is the RP image of impulse signal. (F), (G), (H) are the gradCAM enhanced features of the image based on which ResNet-50, AlexNet and GoogLeNet predicted the class of the image (E) respectively

Table 3: Power quality disturbance prediction result

Signal	AlexNet		GoogLeNet		ResNet-50	
Actual PQD signals	Predicted PQD	Predicted Score of PQD	Predicted PQD	Predicted Score of PQD	Predicted PQD	Predicted Score of PQD
Sag	Sag	0.9959	Sag	1	Sag	0.9998
Swell	Swell	0.9987	Swell	0.9999	Swell	0.9999
Interruptions	Interruptions	1	Interruptions	1	Interruptions	1
Impulse	Sine	0.0209	Sine	0.1944	Impulse	0.9648
Oscillatory Transients	Oscillatory Transients	1	Impulse	0.2714	Oscillatory Transients	0.9998
Harmonics	Harmonics	1	Harmonics	0.9671	Harmonics	0.8336
Flicker	Flicker	0.9999	Flicker	0.9999	Flicker	1
Notch	Notch	0.9472	Notch	0.9927	Notch	0.9952

The most important feature with a high score is localized on the map, thus highlighting the red area as shown in Fig.1. Figs.1 (A) and (E) are the images of interruptions and impulse data. From Table 3, interruptions data was found to be accurately predicted by all three architectures and the reason behind the accurateness can be seen in Fig.1 where (B) enhances those parts of the image which belong to the features created by ResNet-50; (C) and (D) does the same with AlexNet and GoogLeNet respectively.

For the misclassified signal i.e., impulse, Fig.1(E) was fed to the ResNet-50 resulting in accurate prediction of it as an impulse signal, which is visually explained using the features highlighted in (F). On the other hand, the AlexNet in (G) and GoogLeNet in (H) falsely predict impulse as sine. A very soft claim can be presented here that the number of features used in AlexNet and GoogLeNet is more elaborated and sometimes may result in misjudging the classes whereas ResNet-50 uses more compact features, therefore, succeeding in classifying power quality disturbances signals.

6.0 Conclusions

The current investigation deals with the comparative evaluation of the application of a transfer learning methods that use the recurrence plot methodology to distinguish between different PQD signals. The transfer learning techniques such as ResNet-50, AlexNet, and GoogLeNet were compared and evaluated for the suitability of classifying PQD signals. The architectures were tested on randomly selected signals. Resnet-50 was found to accurately identify all the eight classes of PQD signals. On the other hand, GoogLeNet and AlexNet were associated with false classification of PQD signals. Thus, a conclusion was obtained indicating ResNet-50 as the best model to work with power quality disturbance detection. Accuracy, classification probability, and explainability through GradCam - an explainable AI technique were implemented as a grading reference for the comparative evaluation. Further research is being carried out to extend the present work for identification of other mixed PQD signals.

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