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Comparative Analysis of Convolutional Neural Network and Multilayer Perceptron on Power Quality Classification

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Abstract. Power quality classification is essential for identifying and categorizing various power quality issues within electrical systems. With the increasing integration of electronic devices into power grids, including converters, rectifiers, and inverters, the significance of real-time monitoring and fault prediction has grown. This paper explores the application of image classification techniques, specifically Convolutional Neural Networks (CNN) and Multilayer Perceptron (MLP), in addressing power quality issues. Using a dataset consisting of signals representing different power quality conditions, models were trained and evaluated based on accuracy and loss metrics. The results indicate that while CNN achieved the highest accuracy and lowest loss, MLP models demonstrated efficiency in terms of computational resources. Additionally, the study discusses the potential of image classification technology in enhancing power quality monitoring and management, with implications for improving energy utilization efficiency and supply quality. The findings highlight the importance of leveraging deep learning techniques for addressing complex power quality challenges and paving the way for the intelligent and automated development of power systems.

Keywords: Convolutional neural network; multilayer perceptron; power quality classification.

1. Introduction

Identifying and categorizing different power quality issues within the electrical system is what Power Quality Classification is all about. Nowadays, the issue of power quality cannot be ignored. In the construction process of new power systems with new energy sources as the main component, the continuous integration of electronic electrical equipment such as converters, rectifiers, inverters, and new energy charging piles into the grid can easily lead to them, including voltage swell, voltage sag, harmonic, short interruption, flicker ad so on [1, 2]. Their presence could jeopardize the power system's stability and the normal operation of electrical equipment, being unable to satisfy the needs of users and causing enormous economic losses. Therefore, real-time monitoring, fault prediction, and analysis of power usage are particularly important [3, 4].

The signals can be categorized into two types: Time-domain Signals and Frequency-domain Signals. Time-domain signals are described based on the variations of signals along the time axis. They directly reflect the changes of signals over time, including the amplitude, phase, and frequency variations over time. Frequency-domain signals, on the other hand, are described based on the distribution of signals along the frequency axis. They decompose the signal into different frequency components, reflecting the energy distribution of the signal across different frequencies. These two types of signals have different applications. In this paper, the signals provided are in the time domain.

As these issues are quite common, it is plausible to leverage a substantial amount of data to make classification. Existing models are various, this work will select several of them and make comparisons in this essay. The Convolutional Neural Network (CNN), Multilayer Perceptron (MLP), and Fully Connected Layer are included [5,6]. To make the comparisons in precision, this work sets the same parameters for the learning rate, number of epochs, and the proportions of training, validation, and test sets.

2. Method

2.1. Dataset

This dataset was given as a part of the Amrita Honeywell Hackathon 2021. Signals in the dataset are mostly classified into one of the 5 classes(power quality condition- normal wave, 3rd harmonic wave, 5th harmonic wave, voltage dip, transient wave). Each signal is characterized by 128 data points. The signals provided are in the time domain [7]. The dataset is divided into three subsets: training, validation, and testing, with proportions of 60%, 20%, and 20%, respectively. The generalization capability of models can be evaluated effectively using this reasonable proportion.

2.2. Model

The general structure of the code can be data transformation, model creation, training, and model evaluation. The detailed explanations are as follows.

2.2.1. ADD-in MLP

This model is a Deep Neural network (DNN) based on Fully Connected Layers, which is also called the MLP model [8,9]. Compared to other models, this is one of the simplest neural network models, consisting of multiple fully connected layers, with each fully connected layer connected to every neuron in the preceding layer. The training process of the model consists of steps including Forward Propagation, Loss Calculation, Backward Propagation, and Parameter Update.

The signals provided are in the time domain. Because time-domain signals are described based on the variations of signals along the time axis, and the input data features are the length of the time series, the input data feature dimension here is 128.

The hidden layers are intermediate layers in a neural network between the input and output layers. They are responsible for extracting features from input data and performing nonlinear transformations. In the neural network model, each of the three hidden layers consists of 64, 32, and 16 neurons, respectively. These parameters dictate the neuron count in each hidden layer, thereby shaping the model's complexity and expressive capacity.

When conducting classification tasks, the number of neurons in the output layer typically reflects the number of classes, with each neuron representing one category. In this example, the model's output consists of 5 classes, indicating that the model predicts which one of five different categories the input data belongs to. There are 5 classes here: power quality conditions- normal wave,3rd harmonic wave,5th harmonic wave, voltage dip, and transient wave.

2.2.2. MLP-1

Mlp-1 adopts a fully connected neural network structure, including three hidden layers and one output layer. By rapidly converging to a nearly optimal solution during the training process, the Adam optimizer can enhance the model's training efficiency. Compared to the Add-in MLP, the running time is shorter. Additionally, TensorBoard was used for visualizing the training process, which facilitates monitoring the training progress of the model more intuitively.

MLP-1 and Add-in MLP both employ neural network models for classification tasks, but they differ in implementation details, which are reflected in the choice of frameworks, data processing methods, model structures, implementation of training processes, and optimizers. The model structure of MLP-1 is a custom neural network model named ele_net, which consists of four linear layers and uses ReLU and Softmax activation functions. On the other hand, the Add-in MLP model structure is a simple fully connected neural network model comprising three fully connected layers, also employing ReLU and Softmax activation functions. MLP-1 utilizes the SGD optimizer, while Add-in MLP employs the Adam optimizer.

2.2.3. CNN

First of all, this work utilizes one-hot encoding to process the classification labels, then construct a 1D CNN model suitable for handling time-series data [10]. Popular deep learning libraries such as TensorFlow and Keras are employed in this process, and the use of the TensorBoard callback function facilitates the visualization of the training process and results.

It is worth mentioning that here this work applied Fourier transformation to each waveform in the dataset, plotted it, and printed its spectrogram. The waveforms of the 5 different power quality issues are as shown.

3. Result

3.1. Data Visualization

The data includes waves of different kinds, including normal wave (class 1), 3rd harmonic wave (class 2), 5th harmonic wave (class 3), voltage dip (class 4), transient wave (class 5). Representative examples are demonstrated in Fig. 1.

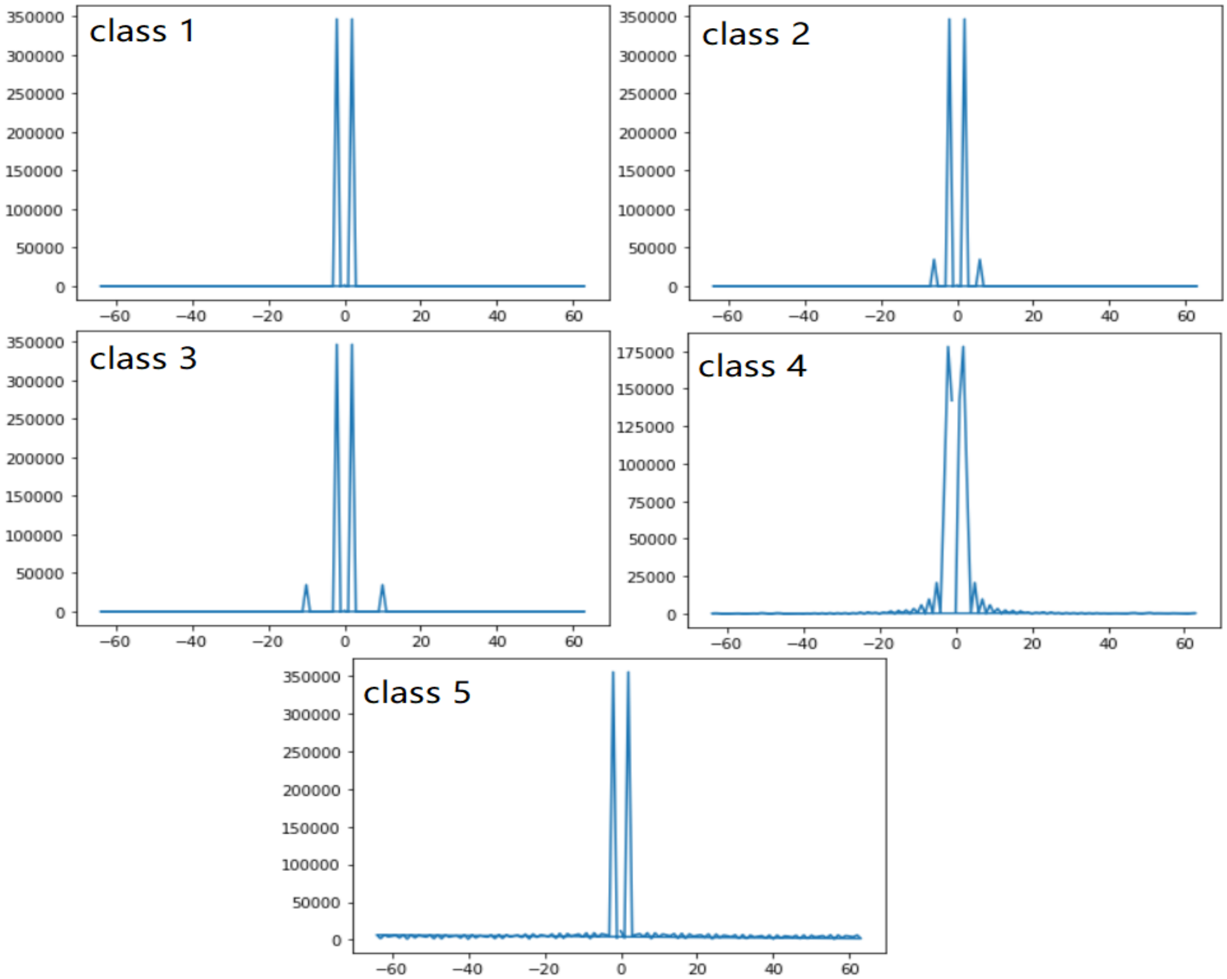

Fig. 1 Representative examples of different waves (Figure Credits: Original).

Harmonics arise from distortions in the voltage and current forms caused by nonlinear loads in the network. Harmonic distortion is commonly encountered in circuits with power electronic components and other electrical loads with nonlinear characteristics. Electrical devices with significant nonlinear characteristics generate a considerable amount of harmonic currents and voltages during operation. If these harmonic currents and voltages exceed the allowable limits of injected harmonic currents at the point of common coupling and the voltage distortion limits of the utility grid, they will pose risks to both power consumers and the power grid.

The 3rd harmonic effects on the power system and equipment mainly include: 1. Overheating of the neutral line; 3. Elevated zero-ground voltage at equipment terminals; 4. Voltage distortion; 5. Excessive temperature rise in transformers; 6. Potential misoperation of residual current circuit breakers.

Voltage swell is the opposite of dips. The voltage rises for a short period of time at a particular point in the power system, with the root mean square (RMS) voltage rising to between 1.1 p.u. and 1.8 p.u., and returning to normal after a brief duration lasting from 10 ms to 1 minute. (1) They may affect the operation of factory machinery and impact the overall power quality.

The most common cause for a voltage swell is a fault on a polyphase transmission line or feeder caused by a line-to-ground connection. Additionally, voltage swell can also occur due to the removal of a large load (such as a large motor) or the connection of a capacitor bank that is too large for the prevailing conditions.

A voltage that is temporarily unwanted in an electrical circuit is referred to as a transient voltage. Its amplitude ranges between a few volts and several thousand volts and its duration spans from microseconds to a few milliseconds. The sudden release of stored energy is the cause of transient voltages, which can be caused by incidents such as lightning strikes and unfiltered electrical equipment, switch bounces, arcing, capacitor banks, or generators being switched ON and OFF. Transient voltages and swells differ in that transient voltages are more powerful and have shorter durations. The most common causes of transients are faulty contactors and lightning.

The term voltage sag refers to a temporary drop in the RMS value of grid voltage at a particular location in the power system, temporarily dropping to 0.5 p.u. to 0.9 p.u. of the nominal system voltage, and recovering to near-normal levels after a brief duration lasting from 10 ms to 1 minute. Voltage sag can lead to a cascade effect between multiple devices, such as cooking hot pot in one room causing the lights in another room to dim. In summary, the causes of voltage sag can be attributed to the startup of large motors or temporary short circuits in power lines.

3.2. Quantitative Comparisons

Based on the accuracy and loss metrics in Table 1, it could be observed that Model 1 achieved the highest accuracy with the lowest loss, indicating superior performance in terms of both classification accuracy and model convergence. However, it also had the longest runtime, which could be a drawback if faster inference times are required.

Model 2 also performed well with high accuracy and a low loss value, although slightly inferior to Model 1. However, it achieved this performance with significantly less runtime compared to Model 1, making it more efficient in terms of computational resources.

Model 3, while still achieving a respectable accuracy, had a higher loss value compared to the other models, indicating less optimal convergence during training. Additionally, it had a runtime that falls between Model 1 and Model 2.

In summary, if computational efficiency is crucial, Model 2 might be the preferred choice due to its relatively high performance and shorter runtime. However, if the highest possible accuracy is required regardless of runtime, Model 1 would be the better option. Model 3, while decent, falls behind the other two models in terms of both accuracy and runtime efficiency.

Table 1. Result comparison of different models

Classifier	Accuracy	Loss	Time
M1:CNN	1	1.1441e-05	1226.4s
M2:MLP-1	0.9998	1.1e-03	182s
M3:Add-in MLP	0.979	7.8076e-02	374.8s

4. Discussion

Utilizing CNN for power quality classification offers advantages such as automated feature learning, hierarchical feature extraction, efficient training, and prediction. Through the mechanism of parameter sharing and local connections, the model's parameter count is significantly reduced, thereby lowering model complexity. This enables more effective handling of signal data in power quality monitoring, enhancing classification accuracy and efficiency.

The structure of the CNN model is relatively simple, partly because image classification problems are relatively straightforward. The fact that its accuracy reaches 1 reflects this point indirectly. In this essay, the author focuses more on describing the simplicity of the model, showcasing, comparing, researching, and summarizing several commonly used methods. However, in practical scenarios, the real data is much more complex than what is presented here. It remains unknown whether simple model structures can effectively fit complex data patterns. Additionally, this method does not involve feature engineering, which may fail to fully exploit the latent information in the data.

5. Conclusion

The image classification technology for power quality issues has wide applications and development potential. It can be applied to anomaly detection and fault diagnosis in power systems, enabling real-time monitoring and analysis to help power operators and users understand the grid situation and take relevant measures to improve power quality. Furthermore, by classifying and analyzing power quality issues, it provides data support for the operation and management of power systems, facilitating the optimization of grid configuration, scheduling, and operational strategies to enhance energy utilization efficiency and supply quality. When applied to power equipment, this technology enables intelligent monitoring and control of power quality, allowing devices to automatically identify and address power quality issues, thus protecting equipment and enhancing its reliability. Many such detection devices are already available on the market. With the advancement of deep learning and artificial intelligence technologies, image classification technology for power quality issues will continue to improve its accuracy and efficiency, offering more possibilities for the intelligent and automated development of power systems.

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