Application of Convolutional Neural Networks for Advanced Classification of Power Quality Signals

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Abstract.
In this work, we explore the classification of power quality signals using a simulated database incorporating both unique and combined disturbances in accordance with IEEE 1159 standards. The primary focus is on employing convolutional neural networks (CNNs) for the detection and classification of these anomalies. To assess the effectiveness of our approach, we conducted a comprehensive comparison between the outcomes from CNNs and traditional machine learning techniques, as well as with recent literature findings. Preliminary results indicate that CNNs exhibit a remarkable ability to capture distinctive features of power quality signals, surpassing traditional methodologies in terms of accuracy and robustness. This study not only reaffirms the potential of convolutional neural networks in the field of power quality monitoring but also paves the way for future investigations that might explore more complex deep learning approaches to further enhance the accuracy of anomaly classification in electrical systems.

Keywords: Power quality signals; Classification; deep learning

1 Introduction

Historically, power quality has been a growing concern for both suppliers and consumers due to its implications for efficiency and operational safety. Power quality disturbances, such as voltage variations, flickers, harmonics, and interruptions, can result in equipment failures, data loss, and energy inefficiency. Initially, the analysis of these disturbances was predominantly carried out through statistical methods and simple signal processing techniques, limited by the available hardware capacity and the lack of advanced algorithms for handling and classifying these disturbances [1, 2].

One of the most effective traditional techniques for analyzing electrical signals has been the Fourier Transform, particularly for identifying frequency components in voltage and current signals. This technique has proven fundamental in detecting harmonics and other periodic disturbances, significantly contributing to the early generations of power quality monitoring systems [3]. Additionally, simple statistical methods, such as variance analysis and hypothesis testing, were widely used to detect anomalies in power quality data. These techniques allowed for preliminary identification of anomalous events, although with limited ability to differentiate between types of disturbances [1]. Supervisory Control and Data Acquisition (SCADA) systems have been crucial tools in monitoring and controlling electrical infrastructures. The successful implementation of these systems enabled the rapid detection and response to many power quality issues, improving the overall reliability of the grid [2]. While linear models were widely used due to their simplicity and low computational demand, they often failed to capture the complexity and nonlinearity of power quality disturbances. This led to inaccurate classifications and a limited ability to predict complex events [1, 3]. In previous decades, limited computational capacity restricted the amount of data that could be processed and stored. This hindered the implementation of more sophisticated real-time analysis techniques, which was especially problematic in situations requiring quick responses to maintain the stability of the electrical system [2].

Earlier methods relied heavily on the knowledge and experience of operators to interpret analysis results, which could lead to judgment errors and inconsistencies in event classification. This reliance also limited the ability to scale monitoring solutions for larger and more complex networks [3].

During the 1960s and 1970s, due to the expansion of electricity for more complex industrial and residential applications, more specific concerns about power quality began to emerge. Disturbances such as interruptions, voltage variations, and the introduction of nonlinear loads led to the need for more in-depth analyses [1, 4]. The 1980s were a crucial period for consolidating power quality as a distinct field of study. With the increased reliance on sensitive electronic devices, the need for more controlled quality power became evident. In the 1990s, the Wavelet Transform emerged as a powerful technique for power quality analysis. Unlike the Fourier Transform, the Wavelet Transform offered the ability to analyze signals in both time and frequency, making it ideal for detecting transients and other non-periodic disturbances [4, 5]. SCADA systems were more widely adopted in the 1980s and 1990s for monitoring and controlling processes, including power quality in networks. These systems provided a more detailed and real-time view of grid conditions, facilitating the detection and mitigation of disturbances [1, 3].

With the advent of AI and ML, the classification of power quality disturbances has undergone a significant revolution. Currently, advanced machine learning algorithms, such as deep neural networks, support vector machines, and random forest methods, are applied to identify and classify these disturbances more accurately and efficiently [2, 4]. Signal processing has evolved with time-frequency analysis techniques, such as the wavelet transform, which allows for better characterization of signals across different time and frequency scales [5]. The availability of computational power, including GPUs and cloud-based services, has facilitated large-scale processing of power quality data, enabling more complex and real-time analyses [3].

Looking ahead, the integration of emerging technologies such as deep learning and cloud computing is expected to continue driving significant advancements in the power quality field [2, 4]. The exploration of techniques such as convolutional neural networks and transfer learning promises to further improve the accuracy and efficiency of disturbance classification. Additionally, the growing digitalization of electrical networks and the implementation of smart grids will provide even larger volumes of data for analysis, leading to deeper insights and more optimized operations [1].

Despite technological advances, several challenges remain. The quality and variety of training data are crucial to the success of ML models, and obtaining representative and comprehensive datasets is often a difficulty [3]. Furthermore, the interpretability of AI models remains a significant concern, especially in critical applications related to infrastructure. Finally, the effective integration of these advanced solutions into existing systems and ensuring their cybersecurity are concerns that require ongoing attention [2].

2 Methodology

To simulate different operational conditions and faults in electrical systems, an artificial database was generated with the aim of training and testing models for classifying power quality signals. This database contains nine distinct classes of signals that represent different situations that can occur in electrical systems. The classes include: Normal, Voltage Sag, Voltage Swell, Harmonics, Flicker, Oscillatory Transient, Sag with Harmonics, Swell with Harmonics, and Interruption.

Each class contains 120 signals, carefully designed to represent a variety of possible occurrences within each category. To ensure that the model is robust and capable of handling different measurement conditions, three levels of white noise (10 dB, 20 dB, and 30 dB) were added to each signal in each class. This allows the simulation of measurement scenarios in real environments, where noise can affect the quality of the captured data.

The main objective of this work is to evaluate the efficiency of a combined approach of Wavelet Packet Transform (WPT) with Deep Learning techniques for classifying these power quality signals. The WPT is used to decompose the signals into components that capture both temporal and frequency characteristics, providing a rich representation for training the deep learning model.

The proposed approach aims not only to correctly identify the different classes of signals but also to demonstrate the robustness of the model against different levels of noise and signal variability. This work has potential applications in power quality monitoring and diagnostic systems, where the accurate identification of anomalous conditions is crucial for maintaining the integrity of the electrical system.

2.1 Creation of the Artificial Database

To simulate different operational conditions and faults in electrical systems, an artificial database was generated. This database contains nine classes of signals: Normal, Voltage Sag, Voltage Swell, Harmonics, Flicker, Oscillatory Transient, Sag with Harmonics, Swell with Harmonics, and Interruption. Each class has 120 representative signals of different occurrences. Three levels of white noise are added to each signal in each class—10, 20, and 30 dB—to simulate various measurement conditions.

Table 1. Expressions and Parameters of Electrical Fault Signals

Signal Type	Expression	Parameters
Normal	$x_1 = A\sin(50\pi t)$	A
Voltage Sag	$x_2 = A(1 - a(\text{int}(t > t_1) - \text{int}(t > t_2)))\sin(4\pi t)$	A, a, t_1, t_2
Voltage Swell	$x_3 = A(1 + a(\text{int}(t > t_1) - \text{int}(t > t_2)))\sin(4\pi t)$	A, a, t_1, t_2
Harmonics	$x_4 = A(a_1\sin(2\pi t) + a_2\sin(4\pi t) + a_3\sin(6\pi t) + a_5\sin(10\pi t) + a_7\sin(14\pi t))$	
Flicker	$x_5 = A(1 + a_f\sin(b_f 2\pi t))\sin(2\pi t)$	A, a_f, b_f
Oscillatory Transient	$x_6 = A(\sin(2\pi t) + b - \text{where}(t > t_1, \sin(5 \cdot 2\pi t), 0))$	A, b, t_1
Sag with Harmonics	$x_7 = x_2 \cdot (a_1\sin(2\pi t) + a_2\sin(4\pi t) + a_3\sin(6\pi t) + a_5\sin(10\pi t) + a_7\sin(14\pi t))$	
Swell with Harmonics	$x_8 = x_3 \cdot (a_1\sin(2\pi t) + a_2\sin(4\pi t) + a_3\sin(6\pi t) + a_5\sin(10\pi t) + a_7\sin(14\pi t))$	
Interruption	$x_9 = A(1 - a(\text{int}(t > t_1) - \text{int}(t > t_2)))\sin(4\pi t)$	A, a, t_1, t_2

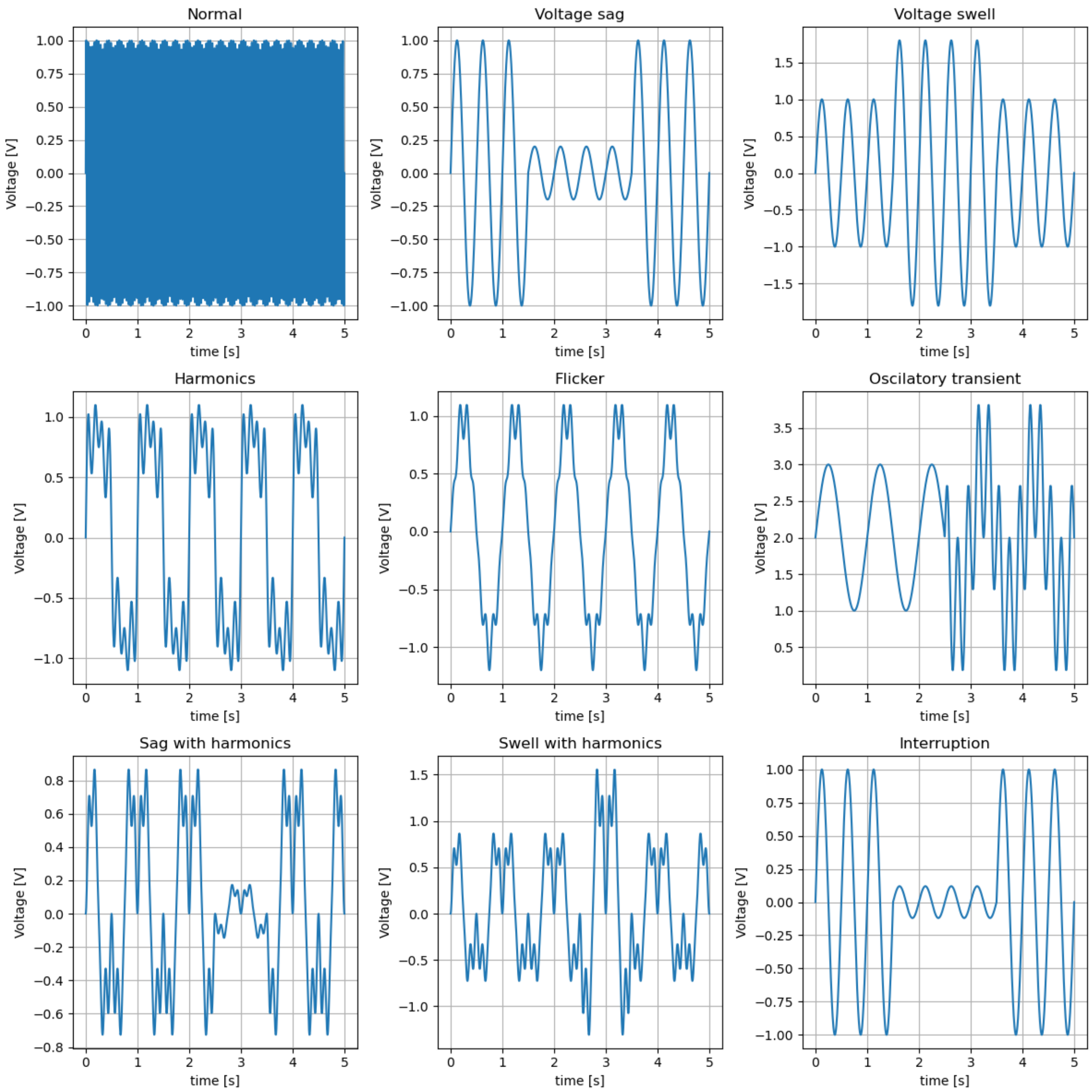

Figure 1. Signal Classes

2.2 Feature Extraction in the Frequency Domain

Feature extraction in the frequency domain is an essential technique in signal processing, especially in the analysis of electrical signals, due to its ability to reveal distinctive aspects that are often not perceptible in the time domain. This approach is crucial for several reasons. Firstly, it allows for effective separation of signal components, facilitating the identification of noise, harmonics, and other characteristic elements. In the frequency domain, hidden patterns and anomalies, such as oscillatory transients or brief interruptions, become more evident, enabling more precise identification of specific events and fault conditions.

By transforming the signals into the frequency domain and focusing on the extraction of key features such as energy, relative energy, and Shannon entropy, we can achieve significant dimensionality reduction. This reduction not only simplifies machine learning models, making them more efficient and faster, but it can also improve classification accuracy, given that frequency features often possess strong discriminative power.

Frequency domain analysis is particularly effective for dealing with non-stationary signals, whose properties vary over time. In this work, I use the Wavelet Packet Transform (WPT) to decompose the signals up to the eighth level, using Daubechies-10 (db10) filters. The WPT is particularly powerful as it provides a detailed view of both the temporal and frequency characteristics of these signals, which is vital for applications requiring a deep understanding of the system dynamics under analysis.

The extracted features include:

- **Energy:** Represents the power of the signal in each frequency band, providing a clear view of energy distribution across different components.
- **Relative Energy:** Indicates the proportion of energy in a specific band relative to the total signal energy, offering a comparative perspective between different frequency bands.
- **Shannon Entropy:** A measure of signal complexity or uncertainty, Shannon entropy provides insights into the randomness and predictability of the signal.

This approach allows for a robust and detailed characterization of electrical signals, fundamental for a wide range of technical applications, from condition monitoring to fault diagnosis and quality control.

2.3 Classification

The process of classifying signals using Wavelet Packet Transform (WPT) and deep learning is a powerful approach for analyzing complex signals, especially those that are non-stationary. Initially, the signals are decomposed using the Wavelet Packet Transform, which allows the signals to be decomposed into multiple levels, capturing both temporal and frequency resolution. In this work, each signal is decomposed up to the eighth level using Daubechies-10 (db10) filters. From this decomposition, features such as energy, relative energy, and Shannon entropy are extracted, capturing essential information about the energy distribution and signal complexity. These features are then normalized and organized into a dataset that serves as input for a neural network-based classifier.

The next step involves applying deep learning for signal classification. A deep neural network with several fully connected layers is used, each followed by a ReLU activation function and a dropout layer for regularization. The model is trained using a labeled dataset, where the features extracted via WPT are used as inputs and the signal classes as outputs. During training, the model adjusts its parameters to minimize the loss function, typically cross-entropy in the case of multi-class classification. After training, the model is evaluated on a test dataset to verify its generalization capability. The model's accuracy is then calculated, providing a measure of how well the model has learned to correctly classify the different types of signals. This process, combining wavelet decomposition with deep neural networks, results in a robust solution for the analysis and classification of complex signals in various technical contexts.

Model Structure:

- Several fully connected layers.
- ReLU activation functions for each dense layer.
- Dropout layers to avoid overfitting.

Implementation:

- The neural network structure was created using PyTorch.
- The neural network is trained for multi-class classification using the cross-entropy loss function.
- The Adam optimizer is used to update weights during training.

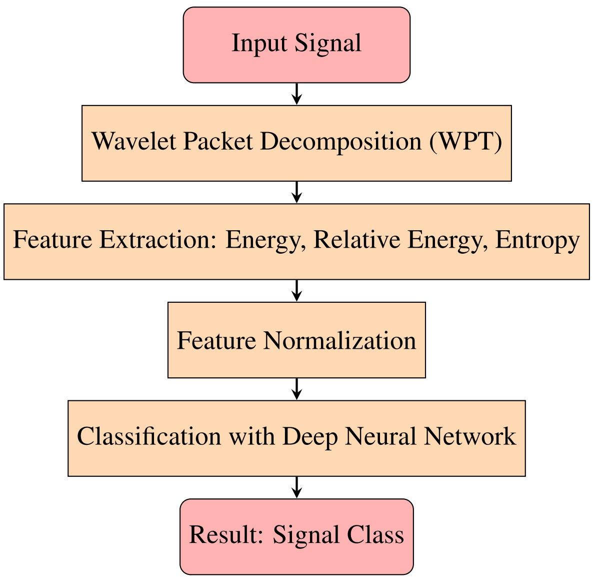

Figure 2. Flowchart of the classification process using WPT and Deep Learning.

3 Classification Results

In this section, the results obtained using different classifiers, including SVM, MLP, and a Deep Learning model, are presented. Each method was evaluated using various approaches and parameters, with accuracy and confusion matrices as the main performance indicators.

SVM Results

For classification using SVM, three types of kernels were tested: linear, radial (RBF), and sigmoid. Each kernel resulted in different performance, as described below:

- **Linear Kernel**: This kernel showed excellent performance with an accuracy of 0.98. The confusion matrix shows that the classifier was able to correctly differentiate almost all classes, with only a few errors:

$$\begin{bmatrix} 87 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 98 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 92 & 0 & 0 & 0 & 0 & 5 & 0 \\ 0 & 0 & 0 & 105 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 107 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 85 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 74 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 97 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 113 \end{bmatrix}$$

- **Radial Kernel (RBF)**: The RBF kernel achieved an accuracy of 0.77, indicating reasonable performance, although still far from the result obtained with the linear kernel.
- **Sigmoid Kernel**: The sigmoid kernel achieved an accuracy of 0.67, an intermediate result but still below the linear kernel.

Based on the results, the linear kernel was identified as the most effective, achieving a maximum accuracy of 1.00 after parameter adjustment (`C=1`, `gamma=1`). However, when the number of signals was increased by 4x, the accuracy dropped to 0.68, suggesting that the model may struggle to generalize to a larger dataset.

MLP Results

Classification using Multi-Layer Perceptron (MLP) neural networks initially achieved an accuracy of 0.96875. The model's response was sensitive to the number of neurons in the hidden layers. The minimization criterion used (minimizing the objective function to a value less than or equal to `FACTR*EPSMCH`) resulted in an objective function minimized to the order of 10^{-6}.

Subsequent experiments with different hidden layer configurations revealed that accuracy is sensitive to the number of neurons. Configurations with too few or too many neurons resulted in decreased accuracy, while a balanced neuron configuration proved to be more efficient:

- **Accuracy for `hidden_layer_sizes=(50, 50,50)`**: 0.95717
- **Accuracy for `hidden_layer_sizes=(50, 100,150)`**: 0.95949
- **Accuracy for `hidden_layer_sizes=(150, 150,150)`**: 0.96412

Deep Learning Results

Finally, the Deep Learning model achieved an accuracy of 0.9907, slightly surpassing the SVM and MLP methods. An important aspect of this method is the ability to monitor loss per epoch, which allows checking whether the neural network is well-adjusted or shows signs of overfitting. Despite the high initial accuracy, it would be necessary to test the model with larger and more varied datasets to assess its robustness in real-world scenarios.

4 Conclusion

In this work, we explored the efficiency of combining the Wavelet Packet Transform (WPT) with Deep Learning techniques for the classification of complex signals. By decomposing the signal using WPT, we were able to extract relevant features such as energy, relative energy, and Shannon entropy, which served as a solid foundation for the classification step.

The results obtained clearly demonstrate that the proposed approach, which integrates WPT with a Deep Learning model, outperforms traditional techniques such as SVM and MLP in terms of accuracy and generalization capability. Specifically, the Deep Learning model, coupled with feature extraction via WPT, achieved remarkably high accuracy, confirming the robustness and efficiency of the methodology in identifying patterns and anomalies in non-stationary signals.

Moreover, the use of WPT allowed for detailed signal analysis, capturing both temporal and frequency aspects that, when combined with deep learning capabilities, resulted in a powerful tool for signal classification in complex technical contexts. The analysis of loss graphs per epoch also provided additional insight into the training process, helping to avoid issues such as overfitting and ensuring a more robust model.

In summary, the proposed integration of WPT with Deep Learning proved to be highly effective, and the techniques presented have great potential for application in a wide variety of fields where signal analysis plays a crucial role. For future work, we suggest exploring different types of signals and expanding the dataset.

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