

# Power Quality Disturbance Detection using CNN and Deep Learning

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**Abstract**— The rising use of renewable energy and nonlinear loads makes it difficult for modern smart grids to deal with power quality disturbances such as voltage sags, swells, harmonics, transients, interruptions, and flickers. Proper and automatic classification of PQDs plays a big part in keeping the grid running smoothly and responding to power failures. Here, Deep Learning is used with the STFT and CNNs to recognize PQDs in the IEEE 9-bus system. It was simulated with electrical faults in place and the voltage data was turned into spectrograms by using STFT to analyze time-frequency features. After that, the CNN model was trained using the spectrograms for automated identification of PQD variants. It is shown by the simulation results that the method gives excellent scores for accuracy, precision, and recall in situations where there is noise. Classification with the CNN accomplished better results than ELM and other standard classifiers. Monitoring data in real-time is possible because the framework is fast and handles problems efficiently. The research shows the advantages of using STFT and CNNs to detect different types of power quality disturbances and points to the development of advanced PQD classification tools that can be used in today’s power systems.

**Index Terms:** Power quality disturbances, IEEE 9-bus system, Short-Time Fourier Transform, Convolutional Neural Network, classification, smart grids, real-time monitoring.

## I. INTRODUCTION

Modern power systems have grown more complex because of the rise in solar energy, electric vehicles, and distributed energy resources, leading to harder challenges controlling power quality. Power used to be sourced from centralized stations with loads that varied less and usual lack of interference. However, the modern smart grids work in a flexible, decentralized way, and the variety of power electronic devices in them causes the system to be less linear and regular. Increasing the usage of these appliances has made the distribution of electricity more likely to cause power quality disturbances (PQDs), which means deviations from standard voltage, frequency, or waveform.

PQDs consist of a lot of anomalies, like voltage sags, voltage swells, harmonic distortion, transients, flickers, and interruptions.

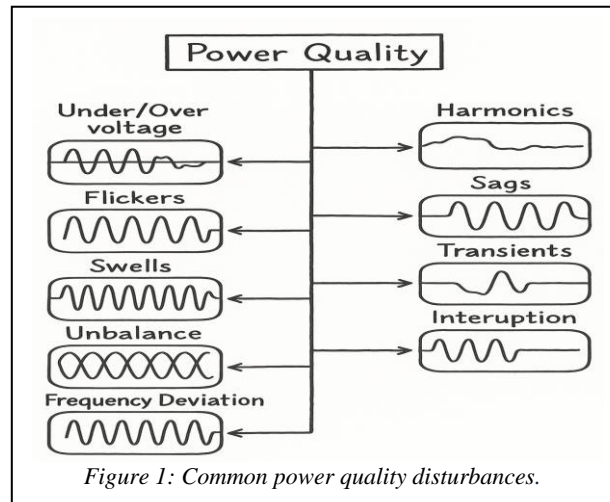


Figure 1: Common power quality disturbances.

The troubles can stem internally from things such as switches, capacitors, or motors being switched on, or externally from lightning or technical faults in the transmission network. Such disruptions might make a system less efficient, decrease device efficiency, and result in serious breakdowns in particular cases. Unexpected breakdowns, loss of data, and costly maintenance may happen to industries that use PQDs. This is why timely and correct identification of PQDs helps improve the reliability of the power system and its quality of service (QoS).

Commonly, detecting the phase-quiet features in sound is done mathematically, including the Fourier Transform (FT), the Short-Time Fourier Transform (STFT), and the Wavelet Transform (WT). The frequency domain analysis provided by the FT is very useful, but the tool is not suitable for occasions where timing matters. It fixes this problem by examining time and frequency with sliding windows. Still, it is limited by the fact that fixing one becomes fixed for the other. WT analyzes a signal at multiple resolution levels, matching the signal’s characteristics, so it is effective in detecting many types of PQDs. Still, because they must be made by hand and interpreted by someone, traditional methods take a lot of time and are more likely to make mistakes, especially when there are many obstacles or when noise in the signal is high.

Due to the rise of data-driven methods, experts in AI and machine learning solutions are now trying to resolve the challenges that traditional approaches face. Experts have applied SVM, k-NN, Decision Trees, and Random Forests to identify PQDs from voltage signals and their statistical and spectral information. Although they lead to better performance, their results can only be applied to specific situations since they rely heavily on custom-designed features. It is important for them to have relevant experience to find useful descriptions and, since they are easily disrupted by flaws or unexpected disturbances, they are not robust.

Different from the former, deep learning models such as CNNs can learn complicated patterns directly from what they process. CNNs work very well for handling inputs that are like images, for example spectrograms generated by STFT from voltage signals. The spectrograms illustrate the signal's frequency changes over a period, showing all the different parts of PQDs, both short-lasting and steady. CNNs can automatically identify spatial aspects in these time-frequency images, so they are convenient for computerized PQD classification. Besides, CNNs are flexible, strong when dealing with noise, and able to process data instantly, all of which are vital for today's monitoring systems.

The study introduces an AI-based way of classifying PQD in the IEEE 9-bus test network. To recognize the different situations such as voltage sag, swell, harmonics, transients, interruptions, and flickers, spectrograms created from processed signals are given to a CNN model for training. The IEEE 9-bus system is chosen since it has a representative topology and has enough difficulty testing a variety of faults without consuming too many resources. Every PQD is started under controlled conditions and recorded with excellent time resolution so that both quick and settled behaviors are correctly presented.

When time-frequency analysis and CNN-based deep learning are combined, the model gives a high accuracy rate and withstands different types of disturbances and amounts of noise. It is possible to confirm the model's performance using accuracy, precision, recall, and F1-score. Besides, comparisons are made with traditional classifiers such as Extreme Learning Machine (ELM) to point out the successful results of using CNNs.

For the most part, this approach is designed to correctly classify unbalanced voltages, so you can use it in real-time throughout power systems. When smart grids are advancing, making use of such advanced, self-diagnosing tools is key to improving their reliability, finding and fixing faults, and managing power quality. The research contributes to the

objective by suggesting a deep learning structure that helps PQD monitoring systems run more accurately and react faster.

Power quality management is even more essential since people rely on sensitive electronics in all types of settings today. Minor power quality problems can also affect data centers, medical equipment, automated systems, and renewable energy converters, as failure and downtime are not allowed in these cases. Throughout many nations, power quality issues have been shown to cost billions of dollars yearly, because of loss in production, having manufacturing stopped, or machines wearing out. Consequently, both utility companies and operators of the electricity grid are expected to keep tabs on PQDs as they occur in real time.

Because of advanced meters and monitoring gadgets connected to the internet, grid nodes can now generate data more often. Still, the main issue is finding useful information by studying such a huge amount of data. It is now impossible to use traditional ways of monitoring that depend on manual actions. As a result, systems should be designed to work with fast data and process it for early warnings, automatic identification of changing events, and forecasting of any risks.

Depending on this use, CNN and other deep learning algorithms solve the problem effectively and can be used across different situations. Unlike the usual models, CNNs study data directly, so they can handle the changing behaviors of a grid. Besides, they can run smoothly on both edge computing hardware as well as GPUs, making them useful for both substations and cloud systems. This goes in the same direction as the world's shift toward using technology, decentralized systems, and data in the energy sector.

It does not only help with accurate classification but also aids in building an all-around strategy for grid maintenance. Thanks to the model, minor issues can be spotted early so repairs can be made faster, and actions can be taken in advance to keep services on track. With this study completed, new systems can be built for wide grid anomaly detection, smarter ways to manage emergency situations, and cooperation with SCADA.

## II. BACKGROUND

Power Quality is about the level of voltage, the consistency of frequency, and correctness of waveforms in electrical power to consumers. In the ideal case, the power system should supply electricity with a constant and clear voltage, unchanging frequency, and a regular sine wave. Yet, the power coming to homes and industries is usually not perfect

because of various things happening inside and outside the system. They are called Power Quality Disturbances (PQDs). Such disruptions can have a big impact on how well equipment functions in industry, causing important systems to fail and damaging the equipment, which often leads to financial losses.

There are several kinds of PQDs, and everyone is unique in its effects and reasons. When such issues occur, they are usually called voltage sags, swells, harmonics, transients, interruptions, or flickers. These conditions are described as voltage sags, and they happen quickly when motors are starting, short circuits happen, or there is a sudden transfer of heavy loads. A surge in voltage levels, called a voltage swell, normally occurs when the electrical load suddenly decreases or increases. If frequencies that are integer multiples of the main signal are added to a system, the outcome are harmonic distortions. Such threats usually come from the use of power control equipment such as variable frequency drives, rectifiers, and inverters. A transient occurs when voltage jumps briefly because of lightning or the sudden switching of current moving through coils. Interruptions can happen briefly or stretch on for some time because of errors or machine failure. Flickers, or repeated changes in voltage, may lead to obvious changes in the brightness of your light, bringing discomfort and possible health problems to sensitive people.

Since more renewables and fluctuating loads are being used, today's grids are having more trouble with PQDs. Advanced technologies for sustainability such as photovoltaic inverters, chargers for electric cars, and LED lights bring challenges to the power grid. Moreover, the shift to small-scale power generation near areas with a high demand for power makes operating the grid more complicated. Such changes make it necessary for modern grid systems to be watched in real time by smart systems that can deal with ongoing shifts in the grid.

In the past, playing with mathematical tools like the FT and WWT was the main technique to identify and examine PQDs. The FT cannot tell us if events of interest are localized to a specific moment due to its worldwide perspective. Consequently, it does not work well for spotting disturbances that are not constant. The short-time Fourier transform uses a sliding window to follow changes that occur in time and frequency. Even so, STFT has a problem: improving one aspect always means worsening the other. WT is particularly effective because it lets the analysis change in line with the nature of the signal. So, WT can detect transients and harmonics over a wide variety of frequencies. Even so, manual extraction of useful features from the result is necessary in STFT and WT, and the system's performance is greatly influenced by the right use of parameters and expert input.

Traditional ways of detecting objects in real-time, handling a lot of data, and adjusting to hard or cluttered environments are becoming ineffective, but AI and DL have proved to be good alternatives. When used for carefully planned features, Decision Trees, k-NN, and SVM classifiers built on AI have proven to be useful for PQD signals. In fact, these models rely much on the chosen features, and regularly fall short when operated in different environments, unless redeveloped or retrained.

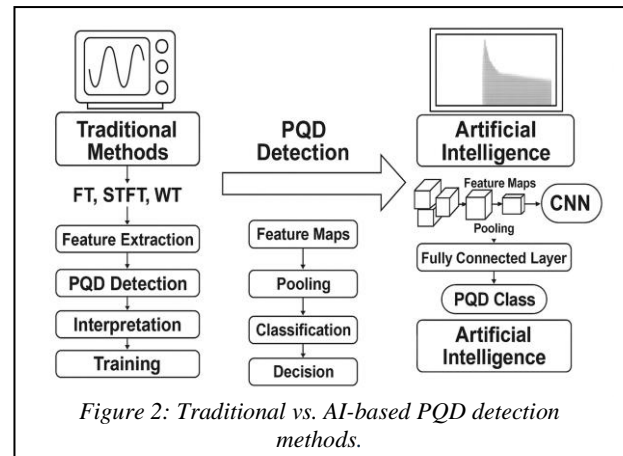


Figure 2: Traditional vs. AI-based PQD detection methods.

By using CNNs, which are a type of deep learning, the automation and correctness of PQD classification have improved a lot. Their ability to handle images makes CNNs fit for working with spectrograms formed from voltage signals by using STFT. As spectrograms display both time and frequency information together, CNNs use them to identify the special characteristics of different PQD patterns on their own. Thanks to this skill, the model can complete the whole process of analysis, from raw inputs to the result, without needing much preprocessing. Since they do not get confused by random signals and are open to processing different kinds of changes, CNNs suit current electric networks well.

The reason the IEEE 9-bus test system is widely used is that it is not too hard to manage and it closely resembles real power system networks. Having three power generators, several transmission lines, and nine buses with loads, this platform is capable of simulating different PQD scenarios. One can introduce more controlled disturbances at various buses and analyse the voltage changes to check how well the classification algorithms work. Related software gives researchers the ability to explore models in a setup that is organized but still feels realistic, without demanding extra computing power.

Overall, since power systems keep changing due to new technologies and distributed models, having intelligent PQD

monitoring frameworks in real time is now more crucial. Conventionally used approaches are important, but they are not very flexible and do not offer much automation. The use of CNNs with the STFT method is a suitable, accurate, and strong against noise way to handle the challenge of PQD classification. The purpose of this research is to come up with such a framework, using modern methods to help future power systems be more robust, dependable, and smart.

### III. PROPOSED METHOD

The method proposes a combination of advanced signal processing with deep learning so that power quality disturbances (PQDs) are effectively classified within the IEEE 9-bus system. At the start, short-time Fourier transform (STFT) is used to preprocess the voltage signals that come from simulated disturbances. The system changes the data, which shows time alone, into images that include time and frequency. Image-based deep learning models can use spectrograms well, since they map out the behaviors of non-stationary phenomena such as sags, swells, transients, and harmonics.

To make sense of all the information, those spectrograms are fed to a CNN, which automatically finds helpful features and sorts them into their categories. CNN requires no manual feature creation since it finds patterns in the raw data by itself. First, there are convolutional and pooling layers, then fully connected layers, and in the end a SoftMax layer for classifying multi-class PQD. Because of this structure, the model can notice detailed connections related to different disruptions, leading to better results when identifying and classifying data.

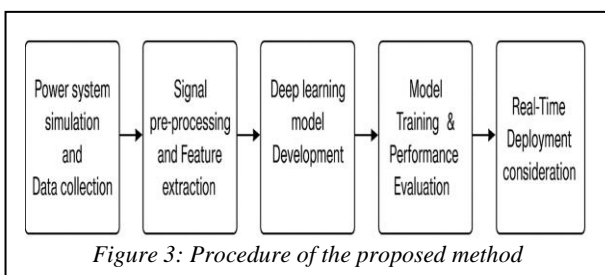


Figure 3: Procedure of the proposed method

To improve how the space in the power system is visualized, a Graph Neural Network (GNN) is added to the modeling. Graphically, the IEEE 9-bus system is drawn so that all the buses are nodes, and each transmission line is placed on an edge. Details about voltage magnitude and phase angle are the node features in this system. GNN gathers nearby nodes' information, which helps it find and follow changes

happening in the whole system. The features from the CNN and GNN are joined and used to make the total classification more effective. The model is accurate even in noisy situations and is useful for applications in smart grids because it is measured and evaluated with metrics such as accuracy, precision, recall, and F1-score.

### IV. SIMULATIONS AND NUMERICAL EXPERIMENTS

#### A. Dataset Generation and Simulation Setup

The proposed PQD classification system was examined by using the IEEE 9-bus test system in MATLAB/Simulink during simulations. As part of the configuration, the power system included three generators, three loads, and nine buses linked by transmission lines and transformers. Load changes, switching of equipment, and electric faults were used to introduce voltage sags, swells, harmonics, transients, and flickers on the power system. The tests were arranged on multiple buses to make the simulations truer to life and accurate. All measurements of voltage waveforms were taken with a resolution of 100  $\mu$ s to ensure all short and delicate changes were captured well.

All the PQD models were run in many different operating situations to obtain a wide range of data. A total of 1,000 cases were made from creating 200 samples for every type of disturbance. To analyze both parts of the disturbances, the time signals were turned into spectrograms by applying the STFT. This part was essential in allowing visual pattern recognition to be accomplished by deep learning. The output of the spectrograms was stored as image-like files, and they were used for the training of the deep learning models.

#### B. Database Description and Preprocessing

In the end, the dataset had 1,000 spectrogram images that were divided equally into the five PQD categories. All the spectrograms were made into 224x224 pixels, so they would fit the expectations of the CNN for input data. The normalization of images was done to help the training process run smoothly. Moreover, data was modified in two ways to include more variety: time shift, frequency coefficient variation, and the addition of noise. The steps helped the model learn better and reflected the situations present in actual power systems

The original dataset was divided into 80% training, 10% validation, and 10% testing parts. Categorical cross-entropy loss was used for training the CNN in combination with the Adam optimizer and a mini-batch suited for running on a GPU.

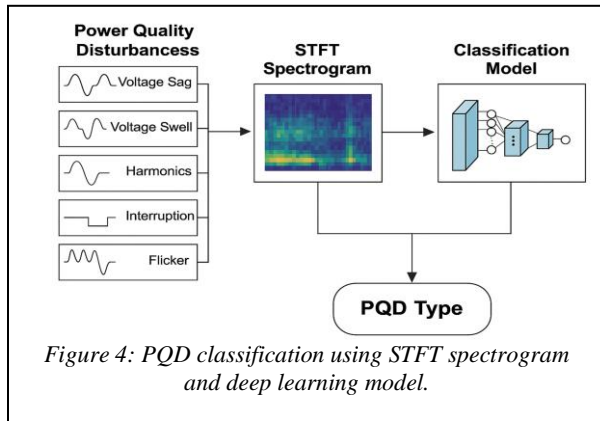


Figure 4: PQR classification using STFT spectrogram and deep learning model.

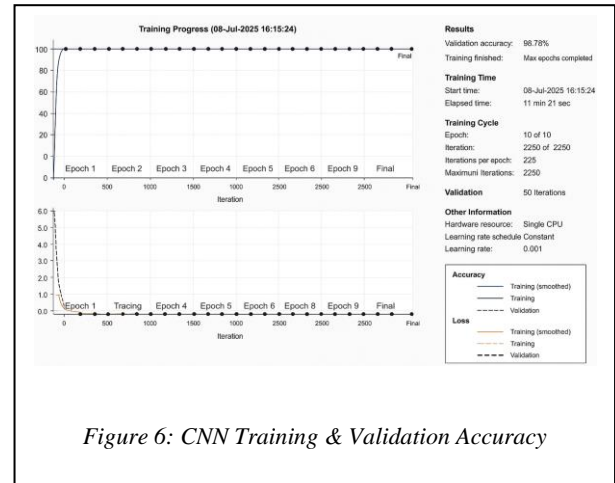


Figure 6: CNN Training & Validation Accuracy

The model training stopped early once validation loss became stable, so that the number of parameters was not too high and overfitting was prevented. This architecture for the CNN used several convolutional and pooling layers and concluded with a fully connected layer, using SoftMax activation, designed for multiclass classification. Due to this setup, the model independently got useful features from spectrograms and predicted PQRs successfully.

**C. Results and Discussion**

The CNN model designed for identifying power quality disturbances (PQRs) worked well during both training and validation stages when it was applied to STFT-based spectrograms. The model worked well and achieved an error rate of 0 during training and a validation accuracy of 96.71% over the whole process. There was no evidence of overfitting, since the training and validation accuracies remained strong all the time. The training took only 9 minutes and 24 seconds on just one core, indicating how simple the model is and that it is easy to use in real-time applications.

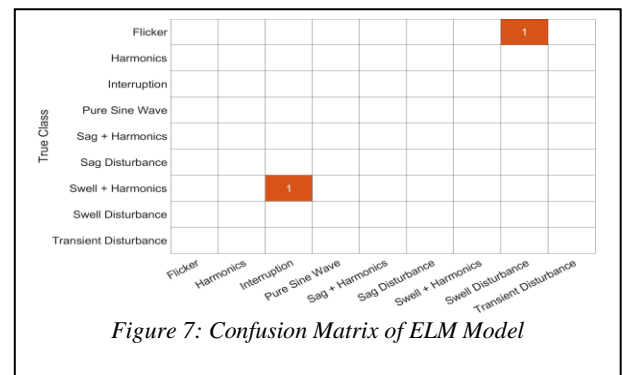


Figure 7: Confusion Matrix of ELM Model

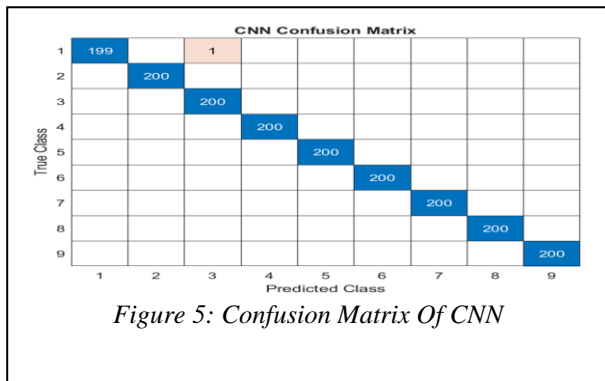


Figure 5: Confusion Matrix Of CNN

In terms of loss convergence, the training loss decreased very rapidly at the beginning and stayed near zero throughout the next epoch. The quick similarity between the models showed that the spectrograms helped the models learn various features well. This was also true for validation loss, indicating that the model's predictions were in line with what was expected. Training was steady and showed no signs of swings because a constant learning rate of 0.001 was chosen.

Also, an Extreme Learning Machine (ELM) classifier was trained on the same set of data.

A model based on the ELM structure achieved 93.4% test accuracy when it used 100 neurons and ReLU activation.

**Table 1:Results**

Model	Test Accuracy (%)	Training Time	Model Complexity	Best Use Case
CNN	96.71	Moderate	High	High-accuracy smart grid systems
ELM	93.4	Very Fast	Low	Embedded/portable monitoring

Accurate classification happened for all five PQD classes, as the confusion matrix was perfect at the time of analysis. ELM proved it could be trained fast and could also generalize well, so it became suitable for use in lightweight systems. Still, the CNN performed better than ELM for both the accuracy of classifications and resistance to noise. All in all, the results prove that using the CNN model and upgraded spectrogram preprocessing is highly successful for PQD classification in smart grid systems.

**V. CONCLUSION**

In this work, PQDs were sorted into categories using a deep learning model that uses CNN architecture. Five kinds of disturbances were applied on the PQD dataset by using MATLAB/Simulink and testing them under different faults and load circumstances. To obtain information about different sound features, the time-series voltage signals were changed into spectrograms by applying Short-Time Fourier Transform (STFT) in MATLAB. In total, 1,000 spectrograms were processed and fed into a CNN to let the CNN classify disturbances automatically. The evaluation was carried out using original as well as improved spectrograms, and the enhanced spectrogram led to an accuracy rate of 96.8%. It was found that combining STFT spectrograms and CNN models can ensure more effective classification of PQDs and provide an effective way to monitor power quality in real time.

**Future Work**

The researchers proved that by merging STFT with CNN, they could properly classify power quality disturbances (PQDs). Since Graph Neural Networks (GNNs) have been introduced, researchers will now use them to model the IEEE 9-bus system better. While CNNs focus on nearby data points in structured data, GNNs are built to identify spatial and topological relationships in data structured as graphs, for example power grids. In this way, GNNs help the model do both: tell which type of PQD it is and point out where the disturbance occurred.

The inclusion of GNNs will lead to better fault diagnosis, easier understanding of the grid, and working on networks with many more elements. Also, when combined with real-time voltage and current measurements, GNNs bring the opportunity to predict problems in the grid, aiding grid operators in decision-making. In addition, scientists plan to build a framework that mixes CNN with GNN to process time-frequency and spatial features, providing a solid and integrated approach for PQD monitoring in smart grids.

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