Research Article

Classification of Power Quality Disturbances (PQDs) Analyzed Using Deep Learning Techniques

Muhammad Saeed[1], Faheem Khan[2], and Usman Humayun[3,⋆]

[1,2]Department of Computer Science, College of Computer and Information Sciences, King Saud University, Riyadh, 11633, Saudi Arabia.; Email: saeedali33@gmail.com, faheemkhan114@gmail.com
[3]Faculty of Computer Science, Bahauddin Zakariya University, Multan, 60000, Punjab, Pakistan; Email: usmanhumayun@bzu.edu.pk
⋆Corresponding author: Usman Humayun (usmanhumayun@bzu.edu.pk)

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Abstract

Power Quality (PQ) issues in distributed generation primarily arise from excessive nonlinear loads inside the system. Identification and categorization are essential to guarantee the reliability of Power Quality Disturbances (PQDs). This paper presented a signal processing and deep learning methodology to categorize Power Quality Disturbances (PQDs) utilizing Discrete Wavelet Transform (DWT), Multi-Resolution Analysis (MRA), and a one-dimensional Convolutional Neural Network (CNN). To expedite training, the performance of the model utilized signal processing-based DWT-MRA to extract 54 features, which were subsequently input into a 1D-CNN. The implementation of 1D-CNN appears to be more dependable than alternative machine learning methodologies. Simulation results demonstrated effective performance and efficient data classification. Consequently, the suggested methodology may herald a new epoch for PQDs in photovoltaic/wind smart grids, yielding more efficient results in the near future.

1 Introduction

Recently, clean energy has garnered increased attention due to technological advancements, as well as evolving consumer energy demands and the utilization of complex loads. Hybrid energy systems are being employed due to the insufficiency of local energy production technologies. PQDs are emphasized as the determinants for power system restrictions such as frequency, voltage, and current [1]. PQDs are a significant concern for both power utilization and consumers, attributable to the minimal losses generated by contemporary power electronics, substantial non-linear loads, rectifiers, and inverters. Identifying PQDs in a renewable microgrid is crucial for delineating the system's decision-making process and ensuring optimal functionality.

The identification of PQDs involves two stages: feature extraction and categorization. Consequently, the feature extraction level identifies distinguishing characteristics of the data. Assuming the data is flawless and achieves superior performance, the reorganization of classification levels results in increased output. Numerous signal-processing techniques may be offered for the analysis of PQDs [2]. Theorems including Short-Time Fourier Transforms, Hilbert-Huang Transform, Kalman Filter (KF), Wavelet Transform (WT), S-Transform (ST), Fast Fourier Transform (FFT), and Curvelet Transform (CT) are utilized in the feature extraction of Power Quality Disturbances (PQDs) [3, 4, 5].

The classification phase identified the types of PQDs based on the analysis from the feature extraction phase. Prior to the 2000s, feature extraction for the PQDs categorization was identified by Artificial Neural Networks (ANN). Additionally, alternative methods such as k-nearest neighbors, fuzzy expert systems, support vector machines (SVM), and evolutionary algorithms were developed to categorize intelligent processes and were significantly utilized in the classification phase of PQDs. Currently, the predominant classifiers employed are Deep Learning Based, utilizing sophisticated image reorganization algorithms for the recognition of PQDs [6, 7, 8]. Recently, numerous academics

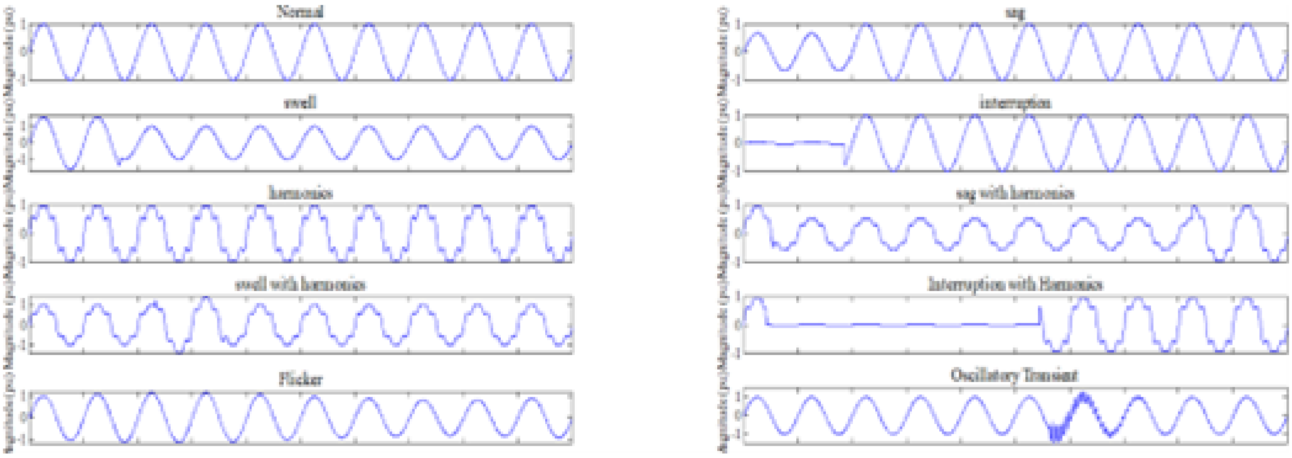

Figure 1: Parametric waveform

have concentrated on power systems due to the substantial implementation of the Solar Photovoltaic (SPV) scheme in the energy sector as given in Figure 1. A subsequent survey indicated that power integration with SPV adversely affected the power system. The efficacy of conventional approaches compared to Artificial Intelligence (AI) systems in substantiating PQDs. The results indicated that the control and response time of AI systems is markedly superior to those of traditional methods [9]. Consequently, the fuzzy c-means (FCM) and ST congregation algorithm have been proposed in PQDs combined with SPV within the power system. The study examined ST-based strategies for sensing PQDs, islanding, interruptions, and grid synchronization with renewable energy sources in a power system. Consequently, a Support Vector Machine, Wavelet Transform, and Independent Component Analysis technique for Power Quality Disturbances detection in a Solar Photovoltaic microgrid [10].

PQ issues arise from non-linear electronic loads and distributed generation connected to the grid. Variations and loads influence the signal's capacity, resulting in non-stationary power quality disturbances. PQDs may be induced by sudden alterations in frequency, amplitude, current, and phase angle. This issue has been addressed via DWT and MRA-based CNN algorithms for the automatic categorization and detection of PQDs. The feature extraction of a PQD signal provides information that facilitates PQD detection. Power engineers can enhance the monitoring and maintenance of power disturbances through the utilization of a precise and efficient feature extraction tool.

2 Methodology

This section discusses Power Quality Disturbances, feature extraction utilizing statistical parameters, and AlexNet. Nonetheless, the Discrete Wavelet Transform, Multi-Resolution Analysis, and Deep Learning methodologies are employed for the classification of Power Quality Disturbances (PQDs).

2.1 Power Quality Disruptions

The proposed methods have been evaluated for classification performance utilizing ten (10) types of parametric equations of PQD signals. The seven distinct forms observed in Power Quality Disturbances (PQDs) include Pure Sine Wave, Normal, Sag, Swell, Interruption, Harmonics, Flicker, and Oscillatory Transients. Moreover, sag with harmonics, swell with harmonics, and interruption with harmonics are the three categories of power quality disturbances (PQDs). Moreover, Table 1 presents parametric equations in line with the IEEE-1159 standard, incorporating parametric variations. Furthermore, the standard PQ waveforms are derived by utilizing the characteristic equation illustrated in Figure 2. The parametric frequency waveforms are 6 kHz with 10 cycles, generated for a maximum of 2000

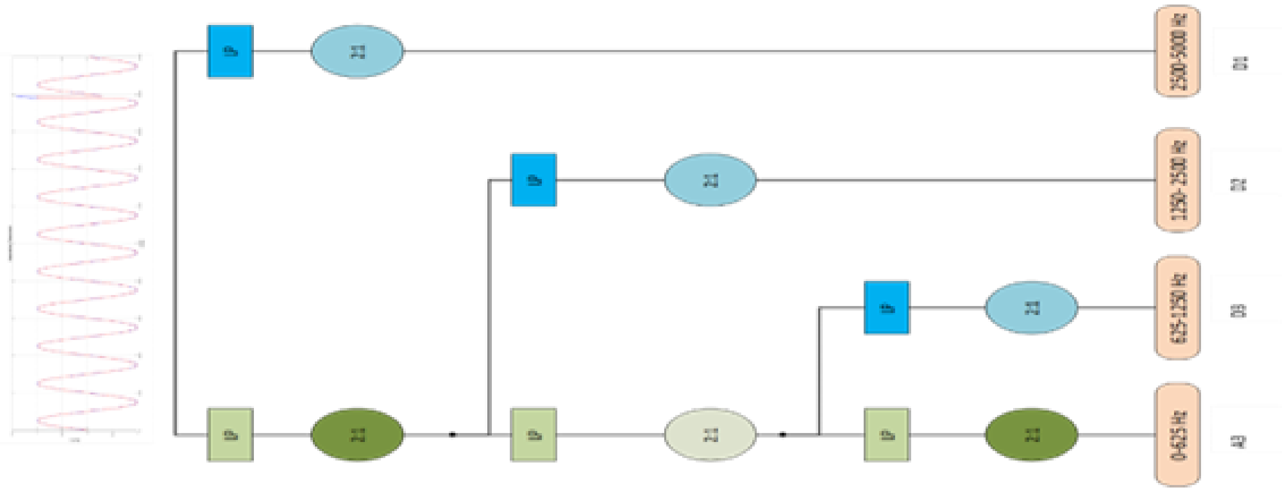

Figure 2: Multi-Resolution

sample points. The parameter A is constant (1 per unit) in all parametric equations of PQDs that denote waveform amplitude. The parameters denote the intensity of swell, interruption, and sag, which exhibit variations based on the nature of disruptions. The duration of the disruption can be specified by the step function within a pure sine waveform.

Waveforms comprising 10 cycles are generated utilizing 2000 sampling points at a sampling frequency of 6 kHz within the comprehensive parametric equations of the PQDs. The A represents the amplitude of the waveform and serves as a constant value (1 per unit). Moreover, the parameter adjusts the intensity of sag, swell, and interruption based on the nature of the disruptions. In a pure waveform, the step function regulates the duration of the perturbation. The 3rd, 5th, and 7th harmonics, with per-unit values ranging from 0.05 to 0.15 of the fundamental magnitude in the overall effective combination, are accountable for harmonic disturbances.

2.2 Discrete Wavelet Transformation

The Wavelet Transform (WT) analyzes local discontinuities in the signal, facilitating the examination of both non-stationary and steady-state signals across many domains. Consequently, PQDs in power systems are non-stationary transients, and the application of WT in PQ research has been recognized as highly significant. The mathematical continuous wavelet transform (CWT) of a continuous signal with respect to the wavelet function is delineated below.

The constant, translation limitations, and measurement representation are illustrated in Figure 1. The parameter scale determines the wavelet length and oscillation frequency. Moreover, the translation factors establish their variable location. Consequently, the series of wavelet factors represents the output at each gauge, indicating the entirety of the transitory signal. CWT will be superfluous for computational analysis with the data suitable for real applications. In equation (2), DWT was identified as more dependable for analyzing the PQDs system as given in Figure 3.

$$DWT(m,n) = \frac{1}{\sqrt{a_0^m}} \sum f(k) \psi \left(\frac{n - kb_0 a_0^m}{a_0^m} \right) \tag{1}$$

The translation and scaling constraints are represented by the integer functions m and n, specifically, $a = a_0^m$ and $b = kb_0 a_0^m$, respectively, while $f(k)$ constitutes a set of discrete points derived from the continuous time signal $f(t)$. An appropriate mother wavelet is crucial for analyzing the outcomes, and it comprises the type of data utilized from the selection of the wavelet transform application.

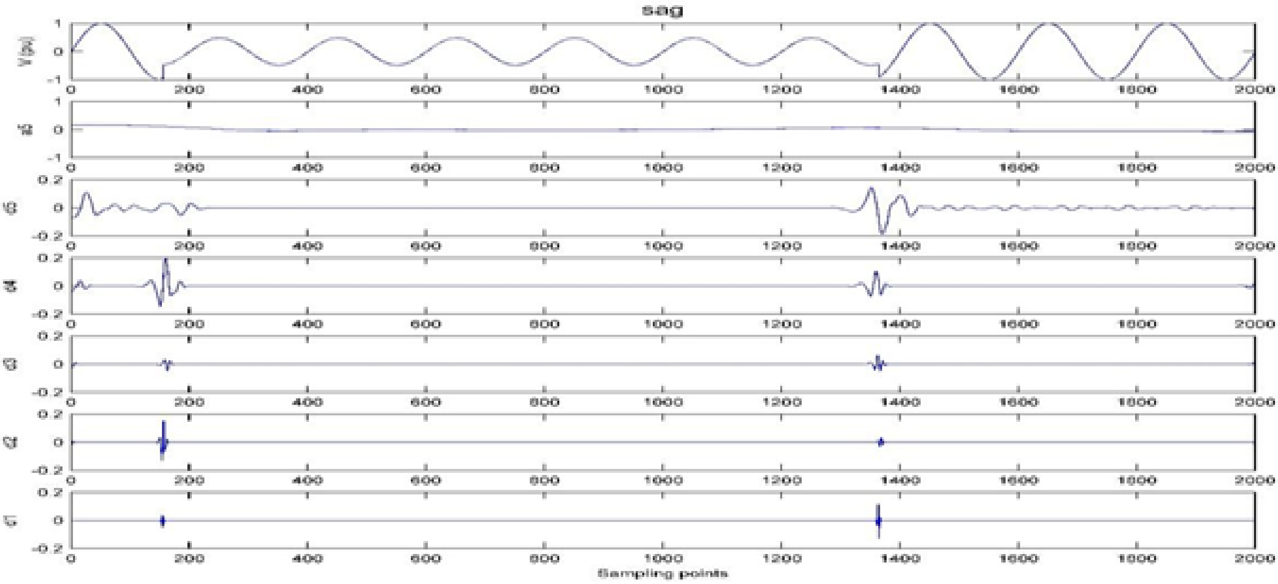

Figure 3: Wavelet coefficient

The mother wavelets analyzed in the PQ analysis include Mexican, Haar, Bi-orthogonal, Morlet, and Daubechies [11].

2.3 Multi-Resolution Analysis

The primary technique employed for the reconstruction and breakdown of signals at different resolution levels is termed Multi-Resolution Analysis (MRA). The decomposition of PQD waveforms use MRA theory due to its simplicity and minimal memory requirements. MRA denotes the signals at various resolution levels. To reconstruct and decompose signals at different resolution thresholds, the fundamental components consist of the scaling function $\phi_{m,n}(t)$ and the orthogonal wavelet $\psi_{m,n}(t)$. For instance, High-Pass (HP) and Low-Pass (LP) filters transmit a time-domain signal $f(t)$ via two filters at each stage. HP filters yield the high-frequency components identified as the detail coefficient (D1), whereas LP filters deliver the low-frequency characteristics of the original time-domain signal approximation coefficient (A1). LP and HP share the same frequency band, with the sampling frequency categorized into two after each decomposition cycle [12].

The signal $f(t)$ can be represented through breakdown into approximations and details via scaling $\phi_{m,n}(t)$ and wavelet $\psi_{m,n}(t)$ as delineated in equations (3) and (4):

$$\phi_{m,n}(t) = 2^{-m/2}\phi(2^{-m}t - n) \tag{2}$$

$$\psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t - n) \tag{3}$$

At the k to j scale, the decomposition of a discrete signal $f(p)$ and wavelet transform based on multiresolution analysis produces low and high-frequency coefficients $D_j(p)$ and $A_j(p)$. The total parameters listed below can reflect the input signal $f(p)$:

$$\begin{aligned} f(k) &= D_1(p) + A_1(p) && (4)\\ &= D_1(p) + D_2(p) + A_2(p) && (5)\\ &= D_1(p) + D_2(p) + D_3(p) + A_3(p) && (6)\\ &= \sum_{j=1}^{l} D_j(p) + A_l(p) && (7) \end{aligned}$$

Here, $j = 1, 2, ..., 6$ represents the stages of the wavelet decomposition. The feature vector size in the signal $f(p)$ is $L + 1$, as indicated in equation (5):

$$f(p) = [D_1, D_2, ..., D_l, A_l] \tag{8}$$

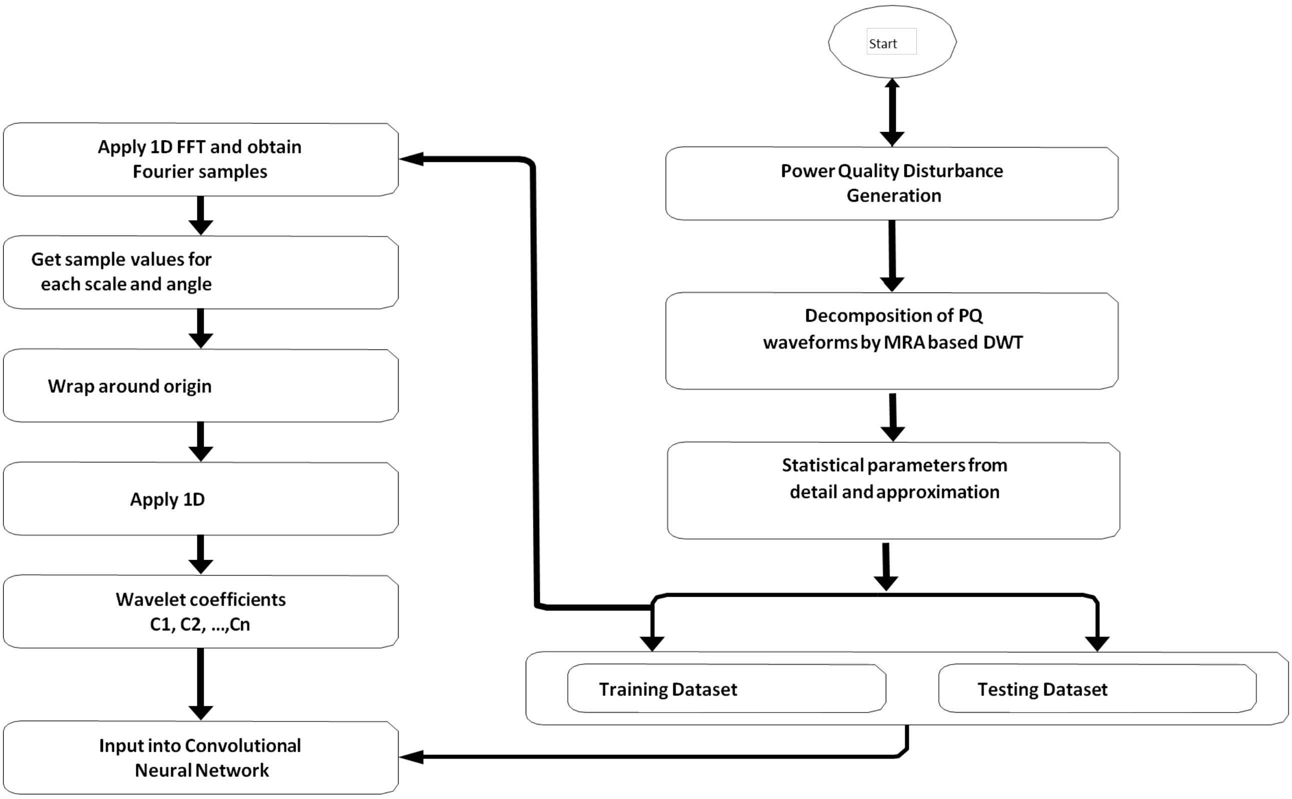

Figure 4: Flow chart of feature extraction

2.4 Feature Extraction Utilizing Statistical Parameters

The statistical elements utilized in feature extraction are documented in prior studies. The mathematical equation presented in Table II can be utilized to calculate the five statistical parameters: Energy (E), Entropy (Ent), Standard Deviation (σ), Mean Value (μ), Root Mean Square (RMS), and Range Value (RG) of the approximation (A) and detail (D) coefficients [13].

The waveforms of PQDs are categorized into six stages for the anticipated feature selection method, yielding six feature coefficients (D1, D2, ..., D6) and one approximation coefficient (A6) as given in Figure 4. The total number of approximation and detail coefficients is 54, from which the most effective features were selected, resulting in good classification accuracy. The statistical feature vector is presented below:

$$F_1 = [E_{D1}, E_{D2}, ..., E_{D6}] \tag{9}$$
$$F_2 = [Ent_{D1}, Ent_{D2}, ..., Ent_{D6}, Ent_{D6}] \tag{10}$$
$$F_3 = [\sigma_{D1}, \sigma_{D2}, ..., \sigma_{D6}, \sigma_{D6}] \tag{11}$$
$$F_4 = [\mu_{D1}, \mu_{D2}, ..., \mu_{D6}, \mu_{D6}] \tag{12}$$
$$F_5 = [RMS_{D1}, RMS_{D2}, ..., RMS_{D6}, RMS_{D6}] \tag{13}$$
$$F_6 = [RG_{D1}, RG_{D2}, ..., RG_{D6}, RG_{D6}] \tag{14}$$

$F_1, F_2, F_3, ..., F_6$ represent the principal feature vector comprising entropy, energy, standard deviation, mean, range values, and the detailed coefficients and approximation values of the Discrete

Wavelet Transform (DWT). Furthermore, the complete dataset of 10 varieties of PQDs influences the classifier's performance, which is present inside the vast feature set. The data must be normalized to a range between 0 and 1. Consider that input data must be processed prior to being fed into the classifier. Furthermore, the feature vector F_i, obtained from MRA, is normalized between 0 and 1 using the min-max approach [14]:

$$Z_i = \frac{F_i - F_{min}}{F_{max} - F_{min}} \tag{15}$$

In this context, Z_i represents the standardized data, whereas F_{min} and F_{max} reflect the minimum and maximum values of the feature vector F_i, respectively. Upon normalization of the data, the whole feature set subsequent to data normalization is presented in equation (7):

$$Feature = [F_1, F_2, F_3, F_4, F_5, F_6] \tag{16}$$

2.5 Deep Learning

In the classification of PQDs, particular feature performances are critically important for the classification domain. PQD was classified using a Deep Convolutional Neural Network (DCNN)-based classifier, and dropout techniques were employed to mitigate overfitting during training. Recently, Deep Convolutional Neural Networks (DCNNs) were created to autonomously extract features from certain aspects of a large-scale dataset, yielding impressive results [15].

2.5.1 AlexNet

The AlexNet Deep Convolutional Neural Network (DCNN) efficiently analyzed 1.2 million images from ImageNet and 1000 image samples, with an expected architectural structure of approximately 60 million parameters and 650,000 neurons. This comprised around three fully connected layers. Additionally, there are three max-pooling layers, five convolutional layers, and two normalization layers. The last layer is equipped with a 10-route classifier program that streamlines logistic degradation for multi-class classification. To mitigate overfitting, the dropout technique is utilized in the final layer, while Rectified Linear Units (ReLUs) are implemented for the activation of fully connected and convolutional layers [16, 17].

The dimensionality of the retrieved features is crucial in the classification domain for categorizing PQDs. The feature selection procedure was executed and implemented on the training data during the algorithm's training phase. A DCNN-based classifier is introduced for the classification of PQD, employing dropout to prevent overfitting during training. Deep Convolutional Neural Networks (DCNNs) have been developed for the automatic extraction of features from extensive datasets, exhibiting remarkable efficacy in object recognition. The classification accuracy and computational speed of the DCNN have been markedly enhanced.

3 Results and Analysis

To evaluate the applied classification approach, seven varieties of single PQDs and three complex PQDs, comprising 2000 samples, will be studied. Artificial single and complex PQD waveforms are generated in MATLAB R2021a using mathematical models. These PQDs were designed arbitrarily and in accordance with the prescribed IEEE standard. PSCAD software was utilized for the production of PQD waveforms. The 6KV distribution network is engineered to produce line faults, including single-line-to-ground, line-to-line, and double line-to-ground faults, resulting in time domain waveforms referred to as swell, interruption, and sag [18].

The methodology is primarily categorized into two steps: feature extraction from signals and the intelligent system DCNN is utilized for PQD classification. The PQD signals are analyzed by DWT-MRA based DCNN techniques. Ultimately, DWT-MRA-based DCNN classifiers are utilized to classify PQD signals. Nonetheless, the experimental procedure was conducted 50 times following the validation of the proposed strategy. In each execution, the dataset is partitioned into training and testing samples, comprising 70% and 30%, respectively.

The following approach is employed for the detection and classification of PQD. The classification of PQD waveforms utilizes a DCNN based on DWT-MRA, with input comprising both Single and Complex PQD signals (x).

STEP 1: A confusion matrix $X_{ij}^{N\times m}$ is generated utilizing the input signal (x).

Where $1 \leq j \leq m$ and $1 \leq i \leq N = N_t - m + 1$. The complete data for the PQD signal was encompassed within the disordered matrix, which was of a specified dimension m.

Step 2: Additionally, the DCNN method is employed for feature selection, while MRA and DWT classifiers are utilized to categorize the PQD and annotate each segment.

A DWT-MRA based DCNN classifier was developed using approximately 2000 samples of 7 simple and 3 complex power quality disturbances (PQD). It extracts the PQD using the provided techniques, thereafter transmitting it to the convolution layer and max pooling following its passage through the former. The process culminates in the final fully connected layer and Softmax classifier, which categorize the signals.

The DWT and MRA techniques are utilized to enhance the classification accuracy of PQD signals. The observed result is 99.37%, given the existence of ten distinct kinds of PQDs. This method's verification employs solely complex and 110 samples for each PQD signal.

The fuzzy methodology achieved a classification accuracy of approximately 98.71% with seven varieties of PQD, utilized alongside DWT for feature extraction. Eight distinct categories of PQD were categorized utilizing the Fuzzy-ARTMAP wavelet neural network methodology, with an average classification accuracy of 99.66%. Furthermore, eleven single and twenty-one complex PQDs were analyzed using a rule-based classifier and sparse signal decomposition (SSD), resulting in accuracy rates of 99.87% and 96%, respectively [19, 20].

To capture multi-scale features and reduce overfitting, a unit structure comprising 1-D convolutional, pooling, and batch normalizing layers is developed, considering the characteristics of the power quality disturbances issue. Numerous units are aggregated in the proposed DCNN to autonomously extract features from extensive disturbance data. The drawbacks of conventional signal analysis and manual feature selection can be readily addressed in the classification of PQDs, as deep learning facilitates the automatic extraction, selection, and integration of PQD features [21, 22].

Although other existing algorithms have a low categorization rate, these techniques have shown commendable classification accuracy. Nonetheless, the majority of current methodologies have been evaluated on individual and intricate PQD signals with limited sample sizes. The technique could be utilized for the real-time analysis of PQD data. Nonetheless, its latency renders it more appropriate for offline applications. The MRA and DWT methodologies are more reliable for analyzing the properties of complex transient (non-stationary) PQD signals [23, 24].

Table 1: Comparison of Results from Various PQD Classification Methods

Ref	Single PQD	Single PQD Accuracy (%)	Complex PQD
DCNN [13]	9	99.89	22
SSA, CT, and DCNN [16]	9	100	22
Deep Learning [18]	5	99.65	2
Rule-based and SSD [21]	11	99.87	21
SCICA [20]	5	-	12
HST, DWT [24]	7	-	2
WT Fuzzy-ARTMAP [19]	6	99.69	2
Proposed Method	7	99.37	3

4 Conclusions and Future Research

An technique utilizing feature extraction and a one-dimensional CNN for the classification of PQDs has been introduced. The suggested DWT-MRA and 1D-CNN have identified both single and numerous types of power quality disturbances (PQDs). The 1D-CNN effectively categorizes data utilizing parameters such as energy, entropy, skewness, standard deviation, mean, root mean square value, and range. The DWT-MRA, based on signal processing, identified the most prevalent distinguishing characteristic that aids the classifier. Artificial single and complex PQD waveforms are seen through application. These PQDs were randomly created in accordance with the suggested IEEE standard. The PSCAD/EMTDC program was utilized for the generation of PQD waveforms. The 6KV distribution network is engineered, and line faults are generated. Utilizing MATLAB R2021a, mathematical models achieved an accuracy of approximately 99.37%. Future research can validate various features of power signals using real-world PQD data. It can classify seven acceptable single PQD signals and three complex PQD signals. Consequently, these findings indicated that the methodologies employed in this work might be applied for the identification and categorization of both basic and complicated PQDs.

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