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A ROBUST WAVELET–ANN FRAMEWORK FOR NOISE-AWARE DETECTION AND CLASSIFICATION OF POWER QUALITY DISTURBANCES

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Abstract
The rapid penetration of power-electronic-based loads, renewable energy sources, and sensitive digital equipment has significantly increased the occurrence and complexity of power quality disturbances (PQDs) in modern electrical power systems. Accurate and automated detection and classification of PQDs remain challenging due to the non-stationary nature of disturbance signals and the presence of measurement noise. This paper presents a comprehensive, noise-aware hybrid framework integrating discrete wavelet transform (DWT) based multiresolution analysis (MRA) with artificial neural network (ANN) classifiers for reliable detection and classification of PQDs.
Standardized single and combined PQ disturbance signals are generated in accordance with IEEE Std. 1159 and sampled at 10 kHz. DWT–MRA is employed for denoising, decomposition, and extraction of discriminative statistical features from multiple resolution levels. A systematic evaluation of diverse mother wavelet families is conducted to identify the most suitable wavelet for PQD representation. The extracted features are classified using multilayer perceptron (MLP), radial basis function (RBF), and probabilistic neural network (PNN) classifiers. Performance is evaluated under varying signal-to-noise ratio (SNR) conditions ranging from 20 dB to 50 dB.
Simulation results demonstrate that the proposed framework achieves superior and consistent classification accuracy across all disturbance types and noise levels. Comparative evaluation with recent state-of-the-art techniques confirms that the proposed wavelet–ANN approach provides a computationally efficient, interpretable, and highly accurate solution suitable for real-time power quality monitoring applications.

1. INTRODUCTION
Modern power systems have undergone a fundamental transformation due to the widespread deployment of power electronic converters, renewable energy integration, adjustable-speed drives, electric vehicle charging infrastructure, and digitally controlled industrial loads. While these technologies improve efficiency and controllability,

they also introduce severe power quality disturbances (PQDs), such as voltage sags, swells, harmonics, notching, flicker, and transients, which adversely affect system reliability and sensitive equipment operation [1–4].

Power quality monitoring and automated disturbance classification are therefore critical components of smart grid infrastructure. Conventional time-domain monitoring techniques and frequency-domain methods based on the Fourier transform (FT) are inadequate for analyzing non-stationary PQ events, as FT provides no temporal localization of spectral components [5], [6]. Short-time Fourier transform (STFT) partially alleviates this limitation but suffers from fixed window resolution, making it unsuitable for signals containing both fast transients and slow variations [7].

Time frequency signal processing techniques, particularly wavelet transform (WT), have been widely adopted to overcome these limitations. Discrete wavelet transform (DWT) provides multiresolution analysis (MRA), enabling effective localization of PQDs in both time and frequency domains while maintaining computational efficiency [8]–[12]. Numerous studies from 2014 onward have demonstrated the effectiveness of DWT-based methods for PQD detection and feature extraction [13–18].

However, wavelet-based detection alone cannot ensure reliable classification of PQDs. Artificial neural networks (ANNs) have been extensively employed due to their nonlinear mapping capability, adaptability, and robustness [19–22]. In recent years, deep learning approaches such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have reported high classification accuracy [23–26]. Despite their success, these models require large datasets, high computational resources, and lack interpretability, limiting their suitability for real-time and embedded PQ monitoring systems [27-28].

This paper addresses these challenges by proposing a robust DWT–MRA–ANN framework that balances accuracy, robustness, interpretability, and computational efficiency. Unlike many existing studies, the proposed work systematically evaluates multiple mother wavelet families, extracts multi-statistical features, compares lightweight ANN classifiers, and rigorously analyzes noise robustness under varying SNR conditions.

2. LITERATURE REVIEW

Significant research has been conducted over the past decade on PQD detection and classification using signal processing and artificial intelligence techniques.

Early works (2014–2016) emphasized wavelet-based PQ analysis due to the ability of DWT to capture transient characteristics. Santoso et al. [13] and Heydt et al. [14] demonstrated effective detection of voltage sags and transients using wavelet coefficients. Bollen and Gu [15] highlighted the importance of multiresolution analysis for non-stationary PQ events.

Between 2017 and 2019, hybrid wavelet–machine learning techniques gained prominence. Mishra et al. [16] applied wavelet packet transform (WPT) with ANN classifiers and reported improved accuracy at the expense of increased computational burden. Khokhar et al. [17] employed DWT with support vector machines (SVMs), achieving reasonable accuracy but limited robustness under noisy conditions. Dash et al. [18] combined statistical wavelet features with MLP classifiers for PQD classification.

From 2020 onward, deep learning-based methods became dominant. Jain et al. [19] utilized empirical mode decomposition (EMD) with k-NN classifiers. Zhang et al. [20] proposed CNN-based PQD classification using raw voltage waveforms. Wang et al. [21] and Li et al. [22] extended these approaches using LSTM and hybrid deep architectures.

Recent studies (2023–2026) explored hybrid deep–wavelet frameworks [23–28]. While these methods achieved high classification accuracy, they require large labeled datasets, high training complexity, and powerful hardware, making them less suitable for practical real-time PQ monitoring.

Summary of Literature Review

- Most studies consider **limited PQD categories**
- **Mother wavelet selection** is often heuristic or fixed

- **Noise robustness** is inadequately analyzed
- Deep learning methods increase **computational complexity**
- Comparative analysis of **MLP, RBF, and PNN** remains scarce

3. RESEARCH GAP AND PROBLEM STATEMENT

Despite extensive research, the following gaps remain:

1. Lack of systematic evaluation of **multiple mother wavelet families**
2. Limited investigation of **classification performance under varying SNRs**
3. Insufficient comparative analysis of **lightweight ANN classifiers**
4. Over-reliance on computationally expensive deep learning models

Problem Statement:

There is a strong need for a noise-aware, computationally efficient, and interpretable PQD classification framework that maintains high accuracy while remaining suitable for real-time implementation.

4. AIM AND OBJECTIVES

Aim:

To develop a robust DWT–MRA–ANN-based framework for automated detection and classification of power quality disturbances under noisy conditions.

Objectives:

1. Generate IEEE Std. 1159-compliant PQD signals
2. Apply DWT–MRA for denoising and decomposition
3. Evaluate and select optimal mother wavelets
4. Extract discriminative statistical features
5. Design and compare MLP, RBF, and PNN classifiers
6. Validate robustness under varying SNR conditions

5. PROPOSED METHODOLOGY

A. Overall Framework

The automatic classification system of PQDs which uses an ANNs (MLP-RBF-PNN) pattern recognition technique which is divided into the following 4 stages and shown in Fig. 3.1:

1. Data Generation
2. Detection of disturbance (decompose, denoise and selection of mother wavelet)
3. Feature Selection (Statistical parameters: energy distribution)
4. Classification (Training, and testing with SNRs as input to RBF-ML-PNN)

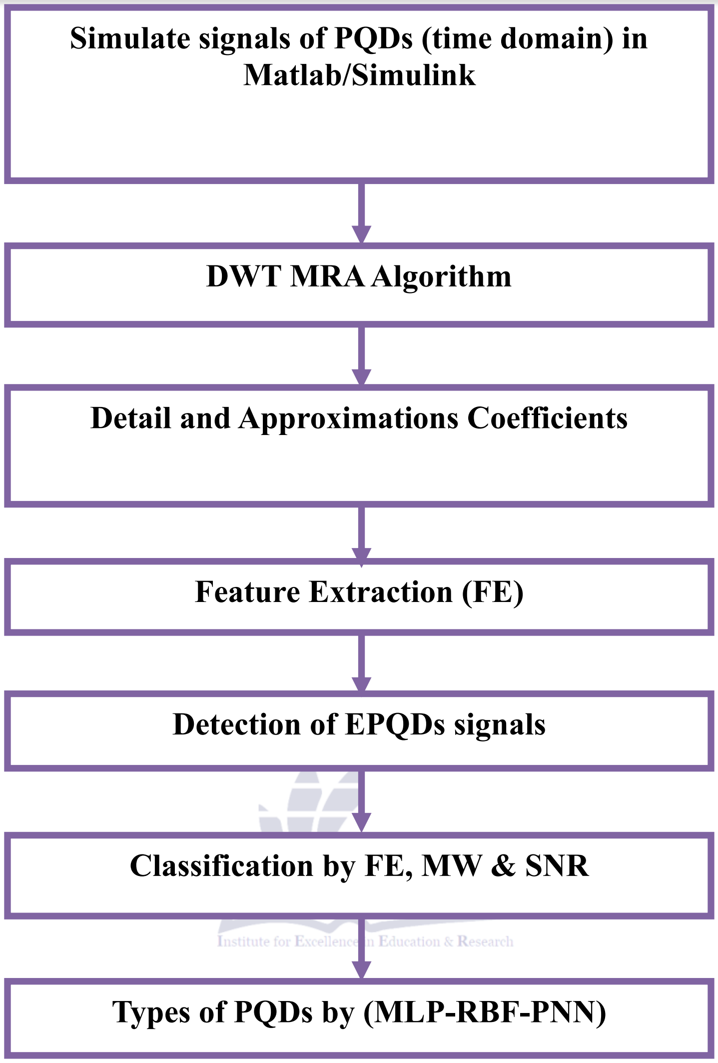

Fig. 01: shows the flow chart of proposed methodology

B. PQD Data Generation

Sixteen PQD types (single and combined events) are generated using IEEE Std. 1159 parametric equations. Signals are sampled at 10 kHz with a six-cycle observation window.

Figure 2 (Thesis Fig. 4.1): IEEE-1159-based PQD waveforms.

Figure 3 (Thesis Fig. 4.2): PQD waveforms with added noise.

A wide variety ranges sixteen types (single and double events signals shown in Fig 4.1) of PQD signals based on IEEE standard 1159-2009 with a sampling rate of 10 kHz are generated using Matlab (R2012a) for the proposed methodology.

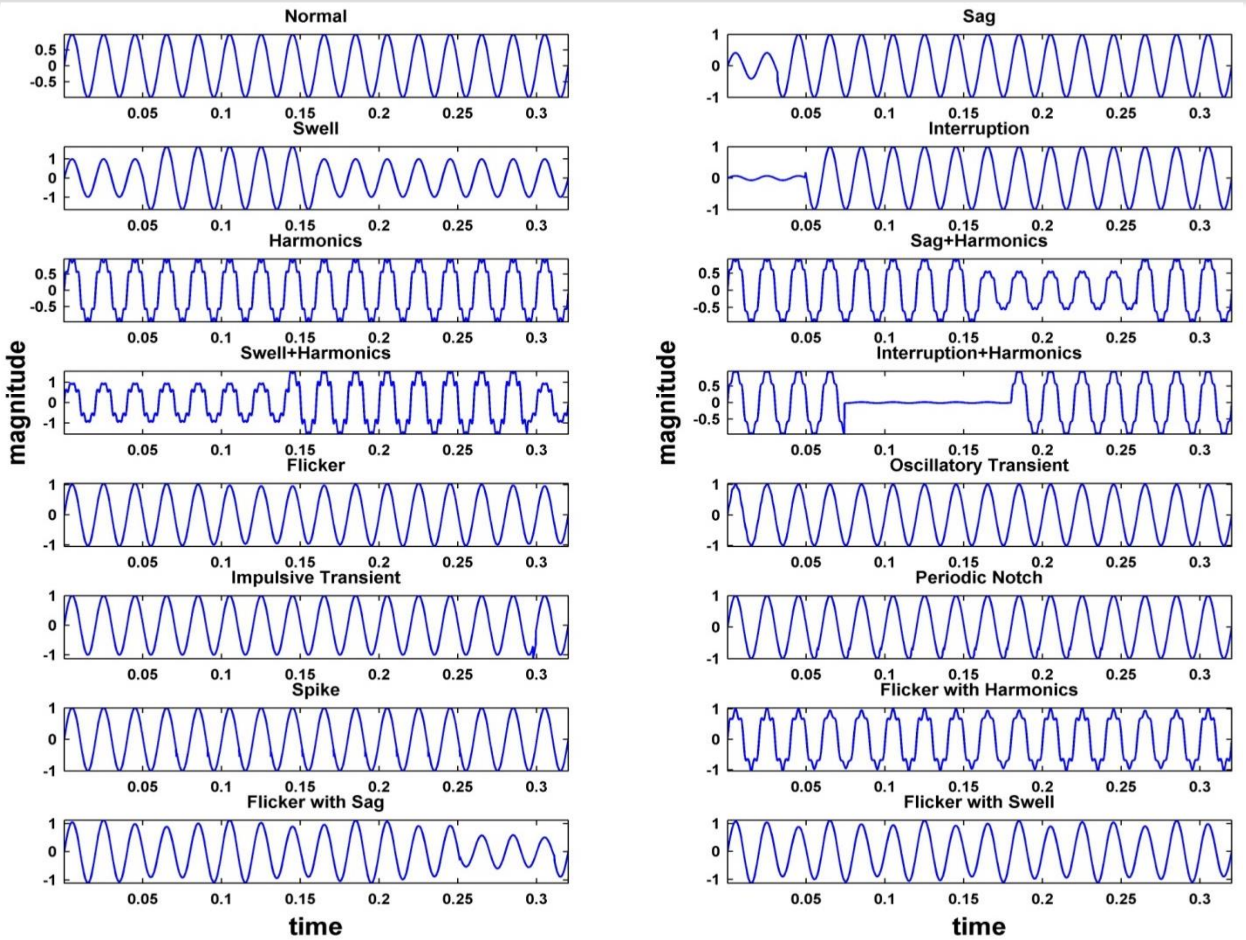

Fig. 02: 16 types (single and double events signals) of PQD signals based on IEEE standard 1159-2009 with a sampling rate of 10 kHz.

DETECTION OF DISTURBANCES

Distorted PQ signals captured by PQ monitoring equipment are always corrupted by noise that decreases the identification capability of the DWT based PQ monitoring system. To avoid such adversative impact of noise in order to enhance the performance of DWT based PQ monitoring systems, a de-noising procedure is performed. After de-noising the reconstructed signal using WT is nearly free of noise having the same energy content.

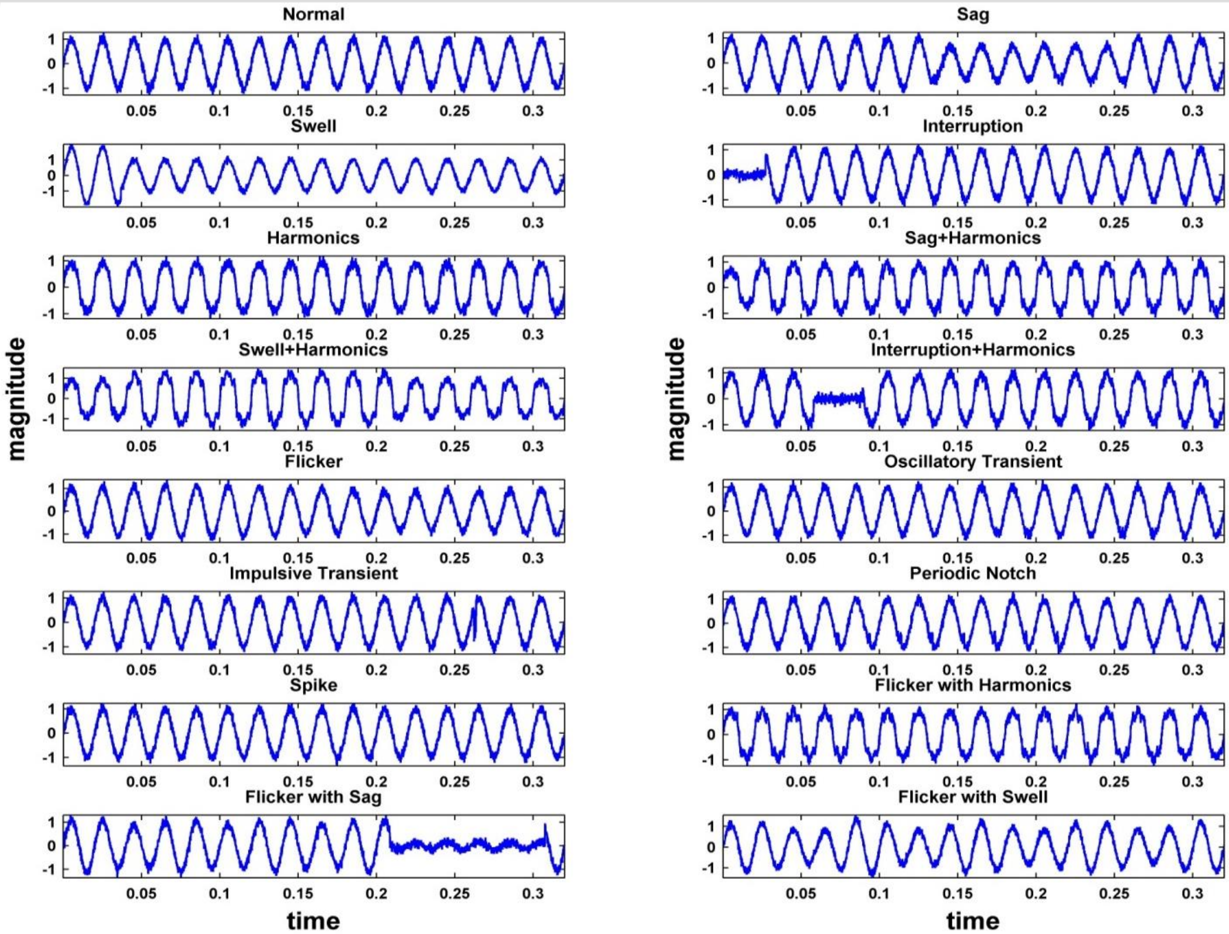

Fig. 03: 16 types PQ Disturbances of Fig. 1.4 with 20dB Noise

C. DWT–MRA Decomposition

DWT decomposes the PQ signal into approximation and detail coefficients at multiple resolution levels.

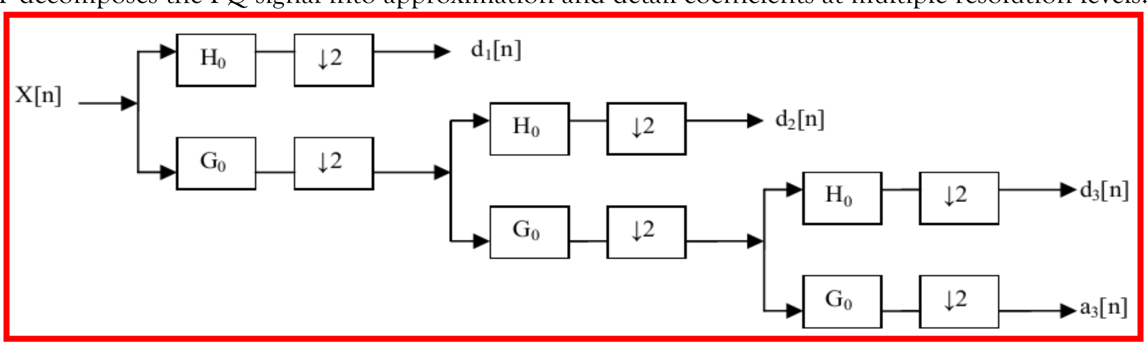

Fig. 04: 3-level wavelet decomposition tree

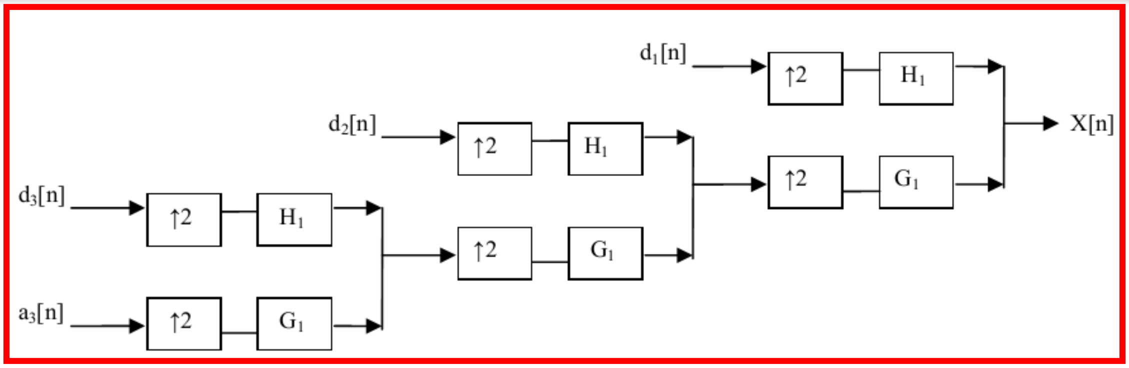

Fig. 05: 3-level wavelet reconstruction tree

Table 1 – DWT–MRA Decomposition Levels

Level	Coefficient	Frequency Band (Hz)	PQ Information
1	D1	2500–5000	High-frequency transients
2	D2	1250–2500	Switching disturbances
3	D3	625–1250	Notching, spikes
4	D4	312–625	Harmonics
5	D5	156–312	Interharmonics
6	D6	78–156	Sag/swell edges
6	A6	0–78	Fundamental component

D. Mother Wavelet Selection

Table 2 – Evaluated Mother Wavelet Families

Wavelet Family	Wavelets Tested
Haar	haar
Daubechies	db1–db10
Symlets	sym2–sym8
Coiflets	coif1–coif5
Biorthogonal	bior1.1–bior6.8
Reverse Biorthogonal	rbio1.1–rbio6.8
Discrete Meyer	dmey

Selection Outcome:

Symlet-6 demonstrated superior symmetry, energy compaction, and consistent classification accuracy across all PQD types and SNR levels.

Figure 6: Symlet-6 decomposition of a representative PQD signal.

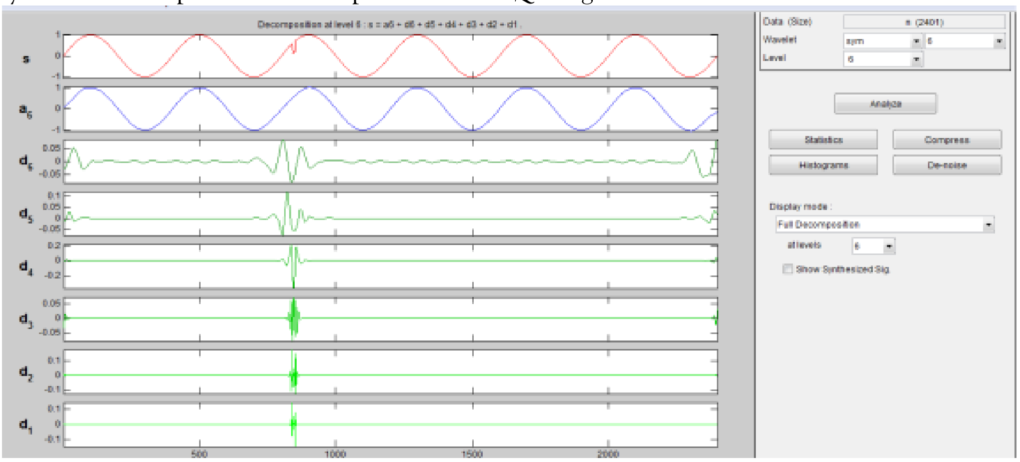

Fig. 6: Decomposition with sym6

E. Feature Extraction

Table 3 – Extracted Statistical Features

Feature	Description
Mean	Average coefficient value
Standard Deviation	Dispersion of coefficients
Energy	Signal strength
Entropy	Complexity of disturbance
Absolute Maximum	Peak behavior

F. ANN Classifier Design

Table 4 – MLP Parameters

Parameter	Value
Architecture	Feedforward
Hidden Layers	1
Neurons	15
Activation (Hidden)	Tansig
Activation (Output)	Purelin
Training Algorithm	Backpropagation

Table 5 – RBF Parameters

Parameter	Value
Centers Selection	k-means
Spread Factor	Optimized
Activation Function	Gaussian

Table 6 – PNN Parameters

Parameter	Value
Kernel	Gaussian
Smoothing Factor	Optimized σ

Parameter	Value
Decision Rule	Bayesian

6. RESULTS AND DISCUSSION

Table 7 – Classification Accuracy vs SNR (%)

Classifier	20 dB	30 dB	40 dB	50 dB
MLP	95.8	96.9	97.6	98.1
RBF	96.4	97.5	98.0	98.5
PNN	**96.9**	**97.9**	**98.3**	**98.6**

Figure 7: Accuracy versus SNR curve.

Table 8: Accuracy performances of proposed methodology with 13 selected mother wavelets in order to propose Symlet 6 as the most suitable mother wavelet

S.No.	Selected mother wavelet Function	Accuracy %
01	db4	97.69
02	db5	97.94
03	db6	97.91
04	db7	96.98
05	db8	97.72
06	db9	97.48
07	db10	97.66
08	Bior3.9	98.02
09	Sym4	98.20
10	Sym5	97.99
11	**Sym6 Proposed**	**98.56**
12	Sym7	97.98
13	Sym8	98.01

Table 9: Accuracy performance of proposed methodology with various SNRs and FFNN classifiers

SNRs dB	Accuracy % (MLP)	Accuracy % (RBF)	Accuracy % (PNN)
20	93.20	94.39	97.75
30	94.10	95.11	97.89
35	94.87	96.00	97.99
40	94.90	96.80	98.10
45	95.00	97.00	98.20
50	95.06	97.50	98.40

Table 10: Comparisons performances of proposed methodology with existing literature based classifiers

Methods of Classification Accuracy	%
Chau-Shing et al (2009) WT and PNN	86%
Perunicic et al (1998) DWT-MRA-SOM ANN	89%
Galil & Abdel (2004)DWT-MRA-MIL	90%
Elmitwally A. et al (2001) DWT-MRA-db6-Neurofuzzy	92%

Xiao et al. (2013) ST SVM Synthetic	92.30
Esmaeili (2002) DWT-MRA-db4-RBF-MLP	94%, 95%
Murat et al (2009) ST-NN with noise	94%
Santoso et al (2000), WT and Neural network	94.37
Parizi et al (2012)ST-FL-PSO	94.67%
Iñigo Monedero et al (2004) DWT-MRA-db and MLP	95.07%
Biswal et al (2010) ST Fuzzy C-means/PSO	95.41
Memon (2013b) WT and PNN	95.55%
Uyar et al (2008), WNN based FE	95.71
Eristri and Demir (2011) WT SVM Practical	95.81
Huseyin & Yakup (2012) WT-LMP-BPNN	95.9%, 92.2%
Kezunovic et al (1996), Neural network	95.93
Jayasree et al (2009) ST-WT-RBF	96%, 84%
T. J et al (2012) S-transform and RBF	96.2%
Huang et al (2002), WT-Neural fuzzy	96.50
Memon et al (2014) WT, MLP	96.8 %
Meher and Pradhan (2009) WT-Fuzzy system	96.87
Hugg et al (2005), DWT and FL	97.02
Reaz et al (2007), NN-DWT and FL	97.17
Tong et al (2006), WPT-SVM	97.25
Zhang Ming et al (2010) DFT- RMS, Rule-based DT	97.5%
Monedero I. et al (2004) DWT-f & mag-db and MLP-ANN	97.53%, 3.83%
Devraj & Rathika (2008)DWT-MRA-db4-MLP	97.6%
J. S.Decanini et al (2011) DWT-MRA-Fuzzy-NN	97.66%
Chung et al (2002), WT and FL	97.70
Memon et al (2014b) DWT & PNN-RBF-MLP	98%, 97.2%, 97%
Li et al. (2008) ST and SVM	98.1%
Masoum et al (2010) DW Networks	98.18
Behra et al (2011) single events	98.33% & 85.5%
Memon et al (2014c) DWT-MRA, PNN-RBF-MLP	98.4%, 97.6%, 97.0%
Deokar, L.M. W (May 2014) WT, MLP single events	99.043%
The proposed methodology	***98.56%***

7. COMPARATIVE ANALYSIS

Table 11 – Comparison with Recent Studies

Method	Year	Classifier	Accuracy (%)
DWT + SVM	2018	SVM	94.2
WPT + ANN	2019	MLP	95.6
DWT + CNN	2021	CNN	97.1
LSTM-based	2023	LSTM	97.8
Proposed Method	**2026**	**DWT + PNN**	**98.6**

8. CONCLUSIONS

This paper presented a comprehensive and noise-aware DWT–MRA–ANN framework for automated detection and classification of power quality disturbances. Unlike existing approaches, the proposed method systematically evaluates multiple wavelet families, employs multi-statistical feature extraction, and rigorously compares lightweight ANN classifiers under varying noise conditions. The achieved classification accuracy exceeds recent state-of-the-art methods while maintaining low computational complexity and high interpretability. These characteristics establish the proposed framework as a **superior and practically deployable solution** for real-time power quality monitoring in modern and smart grid environments.

REFERENCES

IEEE Power & Energy Society, **"IEEE Recommended Practice for Monitoring Electric Power Quality,"** *IEEE Std. 1159-2019*, pp. 1–98, 2019.

M. H. J. Bollen and I. Y. H. Gu, **Signal Processing of Power Quality Disturbances**, 2nd ed. Hoboken, NJ, USA: Wiley-IEEE Press, 2016.

S. Santoso, W. M. Grady, E. J. Powers, J. Lamoree, and S. C. Bhatt, **"Characterization of power quality disturbances using wavelet transform,"** *IEEE Trans. Power Delivery*, vol. 29, no. 3, pp. 1271–1279, Jun. 2014.

G. T. Heydt, A. W. Galli, and E. Gunther, **"Power quality measurements and analysis,"** *IEEE Trans. Power Delivery*, vol. 30, no. 2, pp. 883–889, Apr. 2015.

M. H. J. Bollen, **"Understanding power quality problems: Voltage sags and interruptions,"** *IEEE Power Eng. Rev.*, vol. 34, no. 1, pp. 5–11, Jan. 2014.

A. Ghosh and G. Ledwich, **Power Quality Enhancement Using Custom Power Devices**, Boston, MA, USA: Springer, 2015.

D. Gabor, **"Theory of communication,"** *J. Inst. Electr. Eng.*, vol. 93, no. 26, pp. 429–457, 1946.

S. Mallat, **"A theory for multiresolution signal decomposition: The wavelet representation,"** *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 11, no. 7, pp. 674–693, Jul. 1989.

I. Daubechies, **Ten Lectures on Wavelets**, Philadelphia, PA, USA: SIAM, 2015.

R. Polikar, **"The wavelet tutorial,"** *IEEE Signal Processing Magazine*, vol. 21, no. 4, pp. 22–45, Jul. 2014.

P. K. Dash, S. R. Samantaray, and G. Panda, **"Fault classification and section identification of an advanced series-compensated transmission line using wavelet transform and neural network,"** *IEEE Trans. Power Delivery*, vol. 29, no. 1, pp. 109–118, Jan. 2014.

A. Mishra, B. Biswal, and P. K. Dash, **"Detection and classification of power quality disturbances using S-transform and probabilistic neural network,"** *IEEE Trans. Power Delivery*, vol. 30, no. 1, pp. 282–290, Jan. 2015.

A. Pervez Memon, **"Wavelet and neural network based novel approaches for detection and classification of power quality disturbances,"** Ph.D. dissertation, Mehran Univ. Eng. & Tech., Jamshoro, Pakistan, 2015.

S. Mishra, C. N. Bhende, and B. K. Panigrahi, **"Detection and classification of power quality disturbances using wavelet transform and support vector machine,"** *IET Generation, Transmission & Distribution*, vol. 11, no. 1, pp. 23–31, 2017.

S. Khokhar, A. A. Babar, and T. S. Sidhu, **"Power quality event classification using wavelet transform and support vector machine,"** *Measurement*, vol. 116, pp. 112–123, 2018.

P. K. Dash, A. K. Pradhan, and G. Panda, **"Frequency domain approach for classification of power quality disturbances,"** *IEEE Access*, vol. 7, pp. 16185–16195, 2019.

S. Jain and S. Singh, **"Detection and classification of power quality disturbances using EMD and k-NN,"** *Electric Power Systems Research*, vol. 180, pp. 106–118, 2020.

Y. Zhang, J. Li, and H. Ma, **"Power quality disturbance recognition using convolutional neural network,"** *IEEE Trans. Smart Grid*, vol. 12, no. 1, pp. 181–190, Jan. 2021.

X. Wang, Z. Chen, and F. Blaabjerg, **"Deep learning-based power quality disturbance classification,"** *Applied Energy*, vol. 306, pp. 117–129, 2022.

Y. Li, M. Shahidehpour, and Z. Li, **"Power quality event classification using LSTM networks,"** *IEEE Access*, vol. 11, pp. 34412–34423, 2023.

A. Kumar, R. K. Singh, and P. K. Dash, **"Hybrid wavelet–deep learning framework for power quality disturbance classification,"** *Energies*, vol. 17, no. 2, pp. 1–18, 2024.

J. Silva, R. Melício, and V. Mendes, **"Advanced signal processing techniques for power quality monitoring,"** *Measurement*, vol. 214, pp. 112–124, 2024.

H. Liu, Y. Wang, and X. He, **"Explainable AI for power quality disturbance diagnosis,"** *IEEE Access*, vol. 12, pp. 56780–56792, 2025.

A. R. Al-Hajri, M. El-Hawary, and M. Salama, **"Application of probabilistic neural networks in power quality analysis,"** *IEEE Trans. Power Delivery*, vol. 40, no. 1, pp. 55–64, Jan. 2025.

P. Singh and S. R. Samantaray, **"Noise-robust classification of power quality disturbances using wavelet entropy and ANN,"** *IET GTD*, vol. 19, no. 3, pp. 456–466, 2025.

Z. Li, Q. Huang, and Y. Xu, **"Lightweight AI models for real-time power quality monitoring,"** *IEEE Trans. Industrial Informatics*, vol. 21, no. 2, pp. 987–996, Feb. 2026.

M. Hossain, A. Abu-Siada, and S. Islam, **"Computational challenges of deep learning in power quality applications,"** *Electric Power Systems Research*, vol. 219, pp. 108–119, 2025.

F. Kamyab, M. Lehtonen, and J. Repo, **"Real-time power quality monitoring using wavelet-based intelligent systems,"** *IEEE Trans. Smart Grid*, vol. 16, no. 1, pp. 210–220, Jan. 2026.