A Hybrid Approach for Power Quality Assessment in Multi Source Grid Systems Using Ensemble Machine Learning

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Abstract

Power quality (PQ) assessment is crucial in modern multi-source grids that accommodate thermal, solar, and wind power. The systems tend to exhibit nonlinear and intermittent characteristics and cause disturbances in the shape of voltage sags, swells, harmonics, and transients. Rule-based and traditional signal-processing systems are unable to categorize these disturbances due to high noise and variability present in actual data. In this paper, an efficient PQ analysis is proposed with a hybrid ensemble machine learning technique. A synthetic database of 8000 signals for 16 single and composite PQ disturbances based on IEEE and IEC standards was established. Continuous Wavelet Transform (CWT) was employed to transform 1D signal into 2D time–frequency images to provide better feature extraction. Three ensemble models, Ada-Boost, Light-GBM, and XG-Boost, were trained and tested using clean and noisy (20 dB) data. Ada-Boost demonstrated the maximum accuracy of 99.92% with zero noise and 99.86% with 20 dB noise. Light-GBM and XG-Boost were also satisfactory, indicating accuracies of 95.65%– 98.73% and 96.46%– 98.64%, respectively. The results authenticate that ensemble learning methods offer a reliable and scalable solution to real-time PQ monitoring in smart grid systems that work better than traditional approaches in noisy and complex situations.

*Keywords:* *Power quality assessment, Machine Learning, CWT, Light-GBM*

1. Introduction

Power quality (PQ) evaluation is a key component in the stability, reliability, and efficiency of modern power systems. It entails the quantification of various electrical parameters such as voltage sags, swells, harmonics, flicker, and transients that can affect utility equipment as well as end-user devices [1, 2]. With the increasing demand for high-quality and uninterrupted power, especially in industrial and commercial use, maintaining the optimum quality of power is more important than ever before [3]. PQ assessment by a reliable method helps to detect the disturbances early on, thus it can be acted upon in a timely manner and losses or damages can be prevented [4]. Traditional methods for PQ assessment usually rely on rule-based or signal processing techniques, which while being useful, struggle to deal with dynamic and nonlinear characteristics present in contemporary power systems [5].
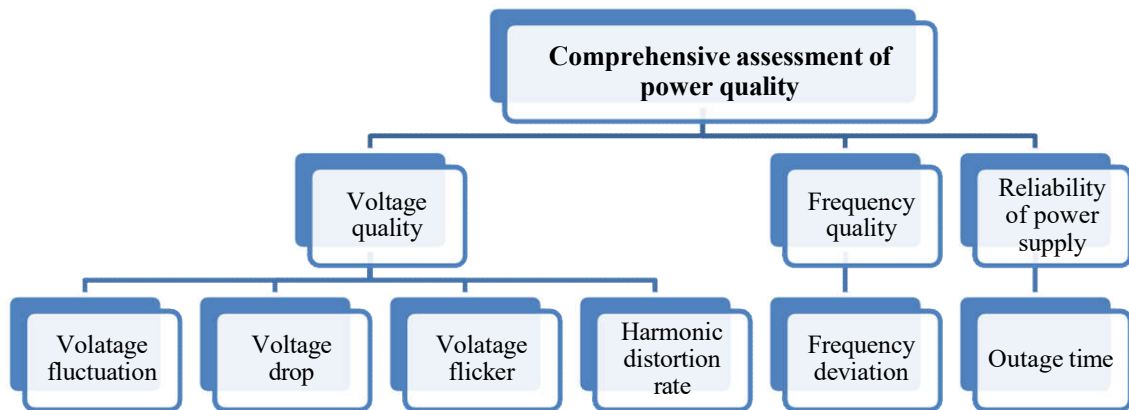
Figure 1: Power quality evaluation system [6].

The PQ evaluation process is also rendered more complicated when multi-source grid systems are considered, e.g., those being power networks with the incorporation of multiple types of energy sources, such as traditional thermal plants, solar photovoltaic installations, wind turbines, and also other distributed energy resources (DERs) [7]. The randomness and intermittence of renewable sources of energy impose new complications in PQ maintenance, such as heightened harmonic distortion, voltage instability, and frequency fluctuation [8]. In these systems, interoperability of disparate sources, and the dynamic load conditions, lead to the incidence of more complex and higher quantities of PQ disturbances [9]. Traditional PQ monitoring equipment can be inadequate to manage these challenges because it lacks sufficient adaptability and is incapable of processing enormous amounts of real-time data efficiently. Therefore, there is increasing demand for more intelligent, data-driven approaches able to manage the uncertainties and variability present in multi-source grids. Artificial Intelligence (AI) and Machine Learning (ML) are gaining traction as prospective solutions in improving power quality monitoring and assessment over the last few years. AI models can learn from past data as well as real-time data and identify, classify, and forecast PQ disturbances more accurately and faster [10].
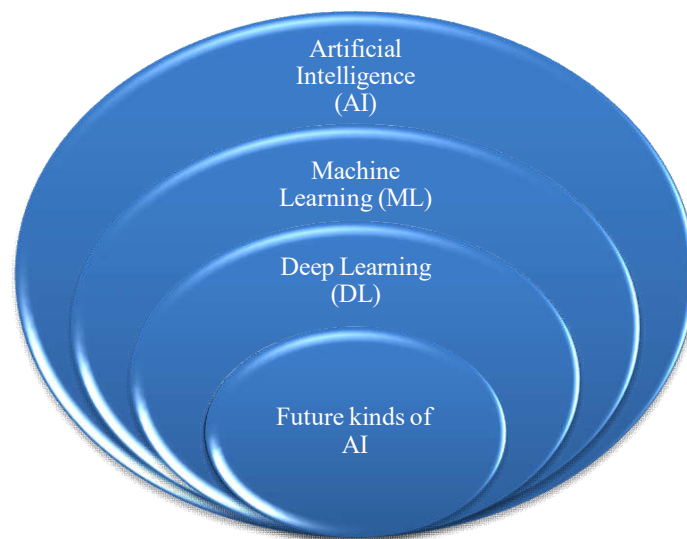
Figure 2: AI development and expansion [11].

However, implementing AI in PQ assessment is not without challenges. The main issues include data quality and availability, model generalization across different grid configurations, computational complexity, and the risk of overfitting [12]. Moreover, a single machine learning model's capability in transforming its hidden features into useful representations of data may indeed be too narrow to realize the key aspects related to all the different parameters of power quality, which is especially true in the case of high-dimensional and imbalanced datasets typically found in power systems.

The mentioned issue necessitates the development of a new class of complex, composite techniques that can handle/challenge difficult situations, e.g., the many-model technique, andmitigate measurement errors for stability due to the ongoing changes. The great efficiency of the hybrid ensemble method is its responsiveness to the new changes that emerge from different sources of a smart grid [13]. The research study displays how this model modifies the classification accuracy of different PQ disturbances in comparison with the ML algorithm. Moreover, the model's scalability and suitability for real-time applications are highlighted, which makes it an adaptable tool for modern smart grid systems. Here are the objectives of the research study are:

- To integrate ensemble ML techniques (such as Ada-Boost, Light-GBM and XG-Boost) to enhance the prediction and classification capabilities of power quality metrics and to evaluate the performance of these models in detecting power quality issues.

- To analyze the performance of various ensemble ML models in terms of precision, recall, and F1-score for detecting power quality disturbances in multi-source grid systems under real-world operational conditions.

- To develop a real-time monitoring system for power quality in multi-source grid systems, using the proposed ensemble approach to facilitate quick detection and mitigation of disturbances such as voltage sags, spikes, and harmonic contamination.

- To compare the ensemble ML model with traditional power quality assessment methods in term of accuracy to noise and data uncertainty

2.   Literature Review

In this section, the authors provide previous study based on a hybrid approach for power quality assessment in multi-source grid systems using ensemble ML.

Jiang et al., (2025) [14] enhanced the accuracy of diagnosing power quality issues in micro grids by using a "Multi-level Global Convolutional Neural Network (MGCNN)" paired with a Simplified double-layer Transformer model. The model employs the "Multi-head Self Attention (MSA)" and MLP parts of the improved S Simplified double-layer Transformer to delve deeper into the signals' periodic global and transient local features; a fully-connected layer and a Softmax classifier are then used to ascertain the classification results. While exploring more complicated aspects, the model successfully preserves the signal's original one-dimensional temporal qualities.

Anwar et al., (2025) [15] presented a new method for identifying and categorizing faults by studying patterns of voltage and current across different phases of a transmission line. Machine

learning methods such as "Random Forest (RF)", "K-Nearest Neighbors (KNN)", and "Long Short-Term Memory (LSTM)" networks are tested using a large dataset that contains a variety of defect scenarios. For better detection accuracy and resilience, an ensemble approach called RF-LSTM Tuned KNN is employed. On a multi-label dataset, RF-LSTM Tuned KNN outperforms both RF (97.50%) and KNN (96.55%), according to the results. The accuracy rate is 99.96%.

With an accuracy of 99.85%, KNN outperforms RF, which comes in second with 99.72% in binary classification.

Liu et al., (2025) [16] provided a solid ensemble architecture for DN-based PQD investigation and event categorization. In order to accurately detect events, these attributes are categorized using Light-GBM. Compared to other benchmark approaches, event identification achieves an average accuracy of 99.33% under different noise levels. In addition, a 98.33% success rate in event detection was achieved using real-time hardware-in-the-loop simulation, proving the method's efficacy.

Mishra et al., (2025) [17] created a novel system for the categorization of PQ disruptions using the Hilbert transform separation method and "Improved Eigenvalue Decomposition of Hankel Matrix (IEVDHM)". The collected features are categorized into 19 distinct types of disturbances using the bagged decision tree, optimizable neural network, and linear support vector machine. Accuracy levels of 92.48%, 91.07%, 88.18%, and 88.01% for clean PQ signals, noisy PQ signals (additive white Gaussian noise) with a signal-to-noise ratio of 60 dB, 40 dB, and 20 dB, respectively, were attained by the bagged decision tree-based classifier.

R. Singh et al., (2024) [18] intended implementing state-of-the-art ML algorithms, particularly "Support Vector Regression (SVR)", to improve the effectiveness and dependability of such systems. Specifically, it achieved an MSE of 2.002 for solar data and 3.059 for wind data, as well as an RMSE of 1.415 for solar data and 1.749 for wind data. Operating expenses were cut by 8.4% as a result of better energy scheduling made possible by this increased precision. As a result, renewable energy utilization increased by 12%, peak load decreased by 15%, and the supply-demand balance improved by 10%.

Sipai et al., (2024) [19] assessed the efficacy of 6 distinct ML algorithms in the classification of PQDs, with statistical information derived from discrete wavelet transform serving as component input. 11 distinct PQDs, each having its own unique set of 5,500 synthetic signals produced in compliance with IEEE 1159-2019, were used for the performance analysis. The "Extra Tree (ET)" classifier demonstrated greater accuracy and resilience when tested on unseen noisy, hardware-generated, and genuine PQD signals, outperforming other classifiers (KNN, RF, DT, LRM, GNB) that used 'haar' wavelet-extracted features.

Baig et al., (2024) [20] showed a voting ensemble method for the classification of 16 PQDs utilizing the DCNN architecture via transfer learning. Using images from four different datasets—one with no noise, one with 20 dB noise, one with 30 dB noise, and one with random noise—MATLAB is used to train and execute four pre-trained DCNN architectures: "ResNet-50, VGG-16, AlexNet, and SqeezeNet". Results show that ResNet-50 with the SE mechanism works well on its own as a classification model, and that using an ensemble method improves its generalized performance even more for PQD classification.

Almasoudi et al., (2023) [21] concentrated on the integration of AI into contemporary power generation networks, especially within the framework of the "Fourth Industrial Revolution 4IR)". More efficient and dependable power systems are in high demand, and AI has emerged as a potential solution to meet this demand. This is accomplished by collecting real-time data from the user's end and looking at the occurrence of internal and external grid faults over a three-year period. The research presented here details the creation of CNN-RNN, CNN-GRU, and CNN-LSTM hybrid models.

3.   Problem Statement

In modern power systems, especially multi-source heterogeneous grid systems consisting of thermal, solar, and wind energy systems, power quality (PQ) maintenance has emerged as a daunting task because of the nonlinear, intermittent, and noisy characteristics of these systems. Conventional power quality assessment methods that consist of rule-based methods and signal-processing methods, however, would fail to detect and identify various PQDs like voltage sags, swells, harmonics, and transients with high accuracy under noisy environments. This ineffectiveness undermines real-time monitoring and mitigation methods under smart grids. Thus, the necessity for having a more efficient, reliable and scalable process that can identify a large variety of PQDs under variability and noise is the pressing requirement in this research scenario. The solution problem under consideration in this work is the development of a hybrid method that leverages ensemble machine learning methods to improve the accuracy, reliability, and scalability of PQ assessment in multi-source heterogeneous grid systems.

4.   Research Methodology

Figure 3 provides an overview of the methodology that has been suggested for PQD classification. It has to have these four main components: the creation of PQD datasets; the modification of time and frequency; the use of ML ensemble learning; and lastly, evaluation. The initial stage involves creating a number of PQD signals using the free and open-source PQD signal generator. The signals are first converted into a time-frequency spectrum of signals using CWT once the data has been formulated. The third phase involves classifying PQDs using a variety of ML ensemble models, such as Ada-Boost, Light-GBM, and XG-Boost. Lastly, several performance assessment matrices are considered in order to assess the model's performance. Following this main part, it will find subsections that elaborate on each component of the suggested structure.
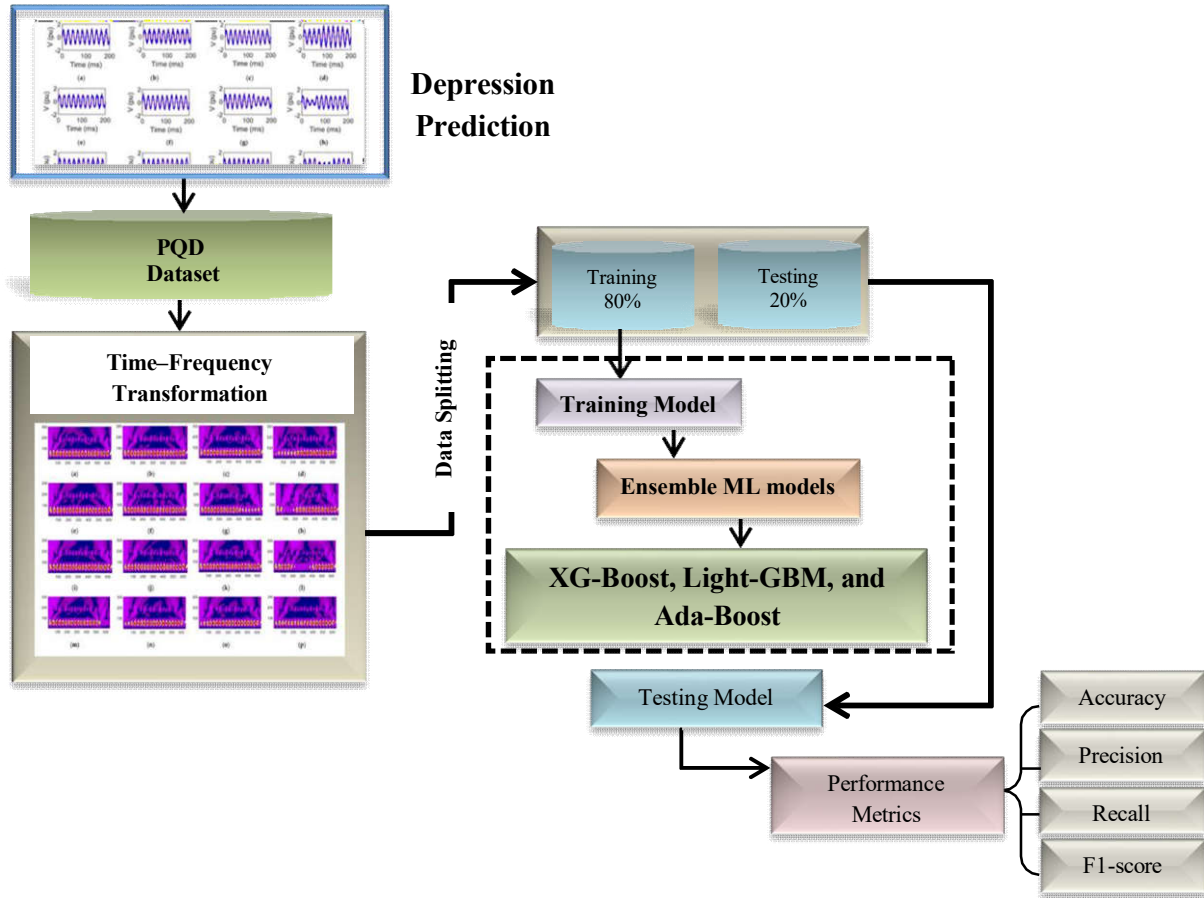
Figure 3: Framework of proposed study

4.1 PQDs Dataset Generation

In this study, researchers build a dataset of sixteen distinct PQD types, encompassing both single and multiple disturbances, in accordance with the requirements of "IEEE-1159, EN 50160, and IEC 61000" [22]. For the purpose of evaluating classifier performance, it has been extensively utilized in earlier research. An open-source PQD dataset generator was used to configure the parameters, the details of which are shown in Table 1.

Table 1: Generating a PQD dataset: parameters

Parameters		
Number of PQD classes	*Flicker*	*Flicker + Harmonics*
	Flicker + Sag	*Flicker + Swell*
	Harmonics	*Impulsive transient*
	Interruption	*Interruption + Harmonics*

	Normal	Notch
	Oscillatory transient	Sag
	Sag + Harmonics	Spike
	Swell	Swell + Harmonics
Each class Samples	500	
Frequency Reference	60 Hz	
Frequency Sampling	3.6 kHz	
Number of cycles	10	
Signal Magnitude	2 p.u.	
Noise levels	20 dB and random noise	

The dataset with dimensions of 8000 × 1600 is the outcome of this method. The produced data is supplemented with random noise ranging from 20 dB in order to mimic realistic settings and allow for comparison analysis. There are sixteen PQDs, and Figure 4 displays an example of them with 20 dB noise and their corresponding class information.
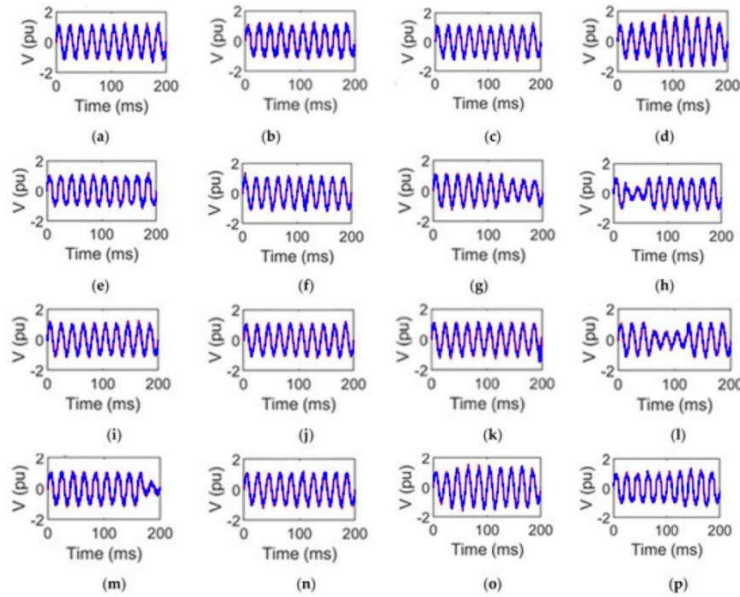
Figure 4: An example of PQDs with 20 dB noise

4.2 Time–Frequency Transformation

A time-frequency demonstration of a time domain signal can be achieved using any number of signal processing techniques. One of these methods, CWT, stands out from the crowd because of

the way it represents transitory signals in terms of time and frequency. Studies using PQDs benefit greatly from CWT because most PQDs are temporary.

They can produce a collection of wavelet basis functions using Equation (1), assuming that $\phi(t)$ is the mother wavelet.

$$\Phi_{a,b} = \frac{1}{\sqrt{a}} \Phi \left(\frac{t-b}{a} \right) \tag{1}$$

Here, Φ is the mother wavelet, while a and b are the scaling factor and translation time, respectively. They could discover the CWT for a certain continuous signal (t) by plugging it into Equation (2).

$$C(a, b) = \frac{1}{\sqrt{a}} \left[\int_{-\infty}^{\infty} (t) \Phi \left(\frac{t-b}{a} \right) dt \right] \tag{2}$$

To get the amplitude scale of the wavelet coefficients after the transformation, use Equation (3).

$$(a, b) = |C(a, b)| \tag{3}$$

Following the application of CWT, Figure 5 displays the time-frequency representations of the signals.

Figure 5: A sample of PQDs with 20 dB noise is shown in time-frequency form

4.3 Ensemble ML models

In this section, the authors define the three ensemble ML methods such as Ada-Boost, Light-GBM, and XG-Boost.

a) Ada-Boost

Ada-Boost (Adaptive Boosting) is well-known not only for its effectiveness in ensemble learning but it is also one of the most popular techniques for classification tasks. The method is about aggregating a series of weak learners that are mostly decision stumps (i.e., trees of shallow depth that have one split) into a single strong classifier [23]. The main concept of Ada-Boost is to train

the weak learners one by one in such a way that every new learner pays bigger attention to those samples that were wrongly classified by the earlier ones. First, each training sample is assigned an equal weight, but the weights of misclassified samples are increased in each iteration so that the subsequent learner focuses more on these "hard" instances [24]. The final model is a weighted aggregate of all the weak models, with those which perform better given greater importance. Ada-Boost is noisy data and outlier sensitive because it attempts to overcorrect misclassifications, but it works well with clean and balanced data sets [25]. It's commonly used in face detection, text classification, and medical diagnosis applications because it's simple and efficient.

b) Light Gradient Boosting Machine (Light-GBM)

Light Gradient Boosting Machine (LightGBM) is a fast and memory efficient gradient boosting framework developed by Microsoft. It has been created with the focus on speed and performance. By using a leaf-wise approach when constructing decision trees (in contrast to level-wise in common gradient boosting methods), it is able to find the best splits for further loss reduction and increase accuracy more efficiently [26]. One of the nice features of Light-GBM is that it employs the histogram-based algorithm for all features. It helps to improve speed and reduce memory consumption by discretizing continuous feature variables into discrete bins. One more thing, it also lets authors perform parallel and GPU learning so that if authors have large datasets with high dimensionality, they can easily deal with them [28]. The Light-GBM framework has the following powerful properties: categorical feature handling, early stopping, and regularization which makes it a very robust and flexible tool for classification, ranking and regression tasks [29]. However, the leaf-wise tree growth that it uses would make overfitting more likely particularly in the case of small datasets.

c) XG-Boost

XG-Boost is a majorly adopted machine learning algorithm that is based on the gradient boosting technique. It follows the approach of building a number of decision trees in a sequence, where each new tree corrects the errors related to the previous ones by decreasing a certain loss function [30]. XG-Boost apart is its efficiency, scalability, and regularization capabilities. It uses both L1 and L2 regularizations for the problem of over fitting, and it can handle natively both sparse data and missing values [31]. XG-Boost employs cutting-edge optimization techniques, namely, parallel computation, tree pruning, and cache awareness, which enable it to be dramatically faster and more precise than traditional gradient boosting implementations [32]. Outwardly, XG-Boost is a complicated algorithm; however, it manages to serve the user with great ease and is well-suited to the classification, regression, and ranking tasks.

| Ada-Boost | Light-GBM | XG-Boost |
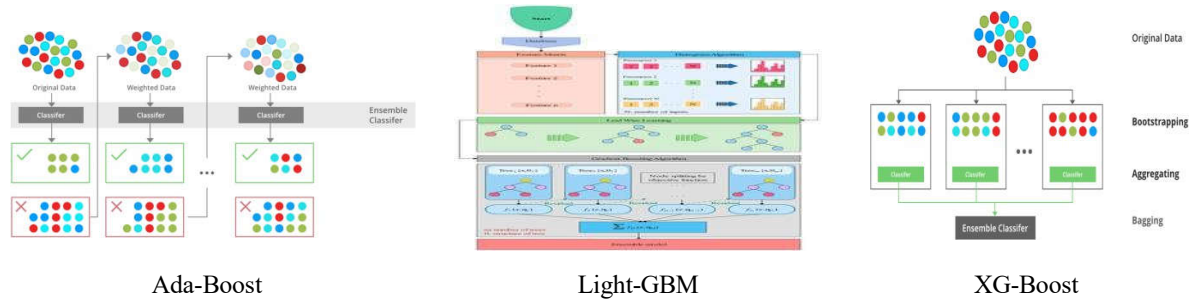
Figure 6: Architecture of suggested models [27]

4.4 Performance Metrics

The evaluation of machine learning algorithms' classification performance relies heavily on accuracy assessment. Some performance indicators were chosen to evaluate the suggested ensemble classification model's efficacy [33].

$$A_{\ Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$R_{\ Recall} = Senstivity = \frac{TP}{TP+FN} \tag{5}$$

$$P_{\ precision} = \frac{TP}{TP+FP} \tag{6}$$

$$F1\text{-}score = \frac{2+Precision+Recall}{Precision+Recal} \tag{7}$$

5. Result and Discussion

The experimental setup that was constructed to implement the suggested approach is discussed in this portion. The findings that were achieved are then presented and discussed. Finally, they compare the performance of the proposed model to that of the previous work.

5.1 Investigational Setup

This section presents the PQD dataset with varying degrees of noise. And here researchers can get the ML ensemble model parameter values as well. The synthetic database that includes sixteen distinct PQD signals, including both single and composite disturbances, is used to evaluate the model's performance. Utilizing MATLAB, the suggested method is applied on a PC model with an "Intel Core i9-9820X CPU (3.3.0 GHz), 32 GB of DDR4 RAM, and an NVIDIA GeForce RTX 2080 8G GPU".

5.2 Training and Estimation of ML Ensemble Models

The subsequent sub-sections provide the training and assessment of each model across various noise levels.

5.2.1 Ada-Boost Classification Results

The training performance of the Ada-Boost model after 100 epochs, with and without noise, is illustrated in Figure 7. The figure graphs the training performance of the Ada-Boost algorithm for 100 epochs under two scenarios: (a) without noise and (b) with 20 dB noise. Under the noise-free scenario (a), the training accuracy takes off in the early epochs and levels off at about 0.97, whereas the validation accuracy lags behind at about 0.94. At the same time, the training loss reduces steadily from an initial value of about 0.65 to below 0.15, reflecting successful model learning.

5.2.1.1 Without noise b) 20 dB noise

Figure 7: Ada-Boost training performance

However, when 20 dB noise is added (b), the training accuracy levels off at 0.89, which is marginally lower than in the noiseless case, while the validation accuracy is 0.91, showing the robustness of the model against noise. The training loss begins at approximately 0.75 and slowly falls to approximately 0.20, while the validation loss falls precipitously in the initial 20 epochs from 0.75 to almost 0.05 and remains low throughout training. This shows that while the addition of noise marginally affects training accuracy, Ada-Boost has good validation performance and generalization ability. The noisy and noiseless data Confusion Matrices (CM) are shown in Figure 8.

Figure 8: CM of Ada-Boost a) Without Noise b) 20 dB noise

5.2.2 Light-GBM Classification Results

Figure 9 depicts the effectiveness of the Light-GBM model for 100 epochs compared to when noise is present and absent. The figure demonstrates the training performance of the Light-GBM model under the two conditions of (a) no noise and (b) 20 dB noise through 100 epochs. In the first part, where noise is not applied (a), the accuracy of the training set quickly went up to 0.88, while the validation set became steady at a mean level lower than 0.85. The loss of the training set was reduced tremendously from over 1.5 at the start of the process to about 0.15, while the loss of the validation set fluctuated first and then stabilized in the range of 0.2 and 0.4, which could be interpreted as the model's generalization has a certain level of uncertainty.

| 5.2.2.1 Without noise | b) 20 dB noise |
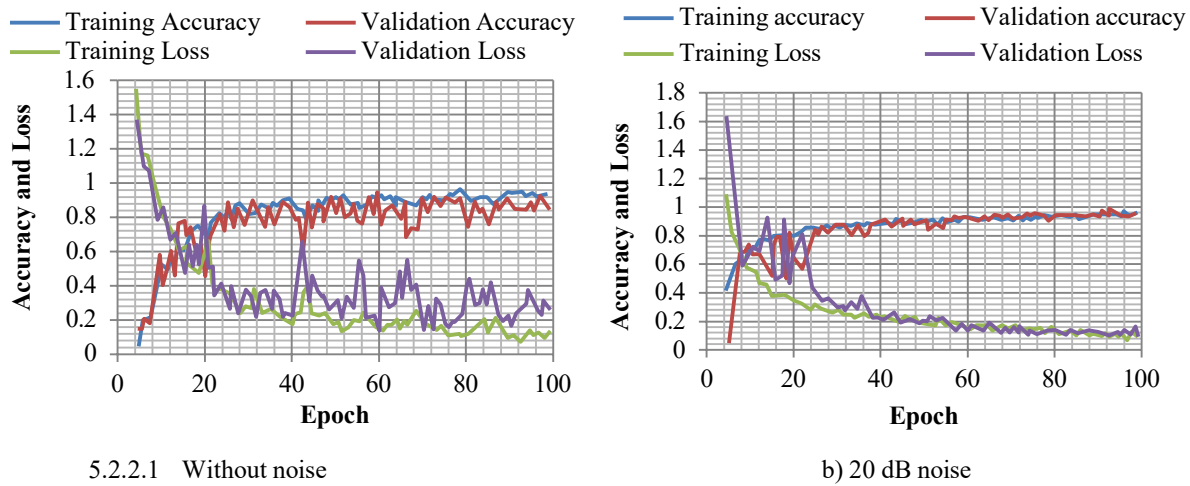
Figure 9: Light-GBM training performance

On the other hand, with less than 20 dB noise (b), both training and validation accuracies trace a more stable trend, approaching 0.87. Training loss decreases steeply from about 1.2 to nearly 0.1, and validation loss traces a steady decrease from 1.6 to less than 0.1 after about 20 epochs, remaining low thereafter. This is an indication that Light-GBM demonstrates excellent learning stability and generalization in both clean and noisy environments, with slightly better validation loss in the 20 dB noise case. CM for noisy and noiseless data are provided in Figure 10.

Figure 10 a) Without Noise:

TRUE \ PREDICTED															
Flicker	480	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flicker+harmonics	0	480	0	0	0	0	0	0	0	0	0	0	0	0	0
Flicker+sag	3	0	473	0	0	0	1	0	0	0	0	3	0	0	0
Flicker+swell	4	0	0	474	0	0	0	0	0	0	0	0	0	2	0
Harmonics	0	0	0	0	480	0	0	0	0	0	0	0	0	0	0
Impulsive transient	0	0	0	0	0	457	0	0	10	0	1	3	0	9	0
Interruption	0	0	1	0	0	0	476	0	2	0	0	1	0	0	0
Interruption+harmonics	0	0	0	0	3	0	0	475	0	1	0	0	1	0	0
Normal	0	0	0	0	0	0	0	0	480	0	0	0	0	0	0
Notch	0	0	1	0	0	0	0	0	16	460	0	2	0	1	0
Oscillatory transient	0	0	0	1	0	5	0	0	1	4	464	0	0	5	0
Sag	0	0	7	0	0	5	97	0	1	3	1	366	0	0	0
Sag+harmonics	0	0	0	0	2	0	1	54	0	0	0	0	423	0	0
Spike	0	0	0	0	0	2	0	0	6	8	1	0	0	463	0
Swell	0	0	0	5	0	0	0	0	4	0	0	0	0	2	469
Swell+harmonics	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	475

Figure 10 b) 20 dB noise:

TRUE \ PREDICTED															
Flicker	480	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flicker+harmonics	0	455	0	0	25	0	0	0	0	0	0	0	0	0	0
Flicker+sag	5	0	467	1	0	0	1	0	0	0	0	5	1	0	0
Flicker+swell	1	0	0	478	0	0	0	0	0	0	0	0	0	1	0
Harmonics	0	2	0	0	478	0	0	0	0	0	0	0	0	0	0
Impulsive transient	0	0	0	0	0	454	0	0	22	3	1	0	0	0	0
Interruption	0	0	0	0	0	0	477	0	1	0	1	1	0	0	0
Interruption+harmonics	0	0	0	0	1	0	0	477	0	0	0	1	1	0	0
Normal	0	0	0	0	0	0	0	0	479	0	0	0	1	0	0
Notch	0	0	0	0	0	18	0	0	461	0	0	1	0	0	0
Oscillatory transient	3	0	1	0	0	5	0	0	4	1	465	0	0	1	0
Sag	0	0	0	0	0	4	1	0	0	1	0	474	0	0	0
Sag+harmonics	0	0	0	0	8	0	0	8	0	0	1	0	462	1	0
Spike	0	0	0	0	0	0	0	1	0	0	0	479	0	0	0
Swell	0	0	0	2	0	3	0	0	0	0	0	0	0	475	0
Swell+harmonics	0	0	0	4	0	0	0	0	0	0	0	0	0	0	476

Figure 10: CM of Light-GBM a) Without Noise b) 20 dB noise

5.2.3 XG-Boost Classification Results

Learning of the XG-Boost model has been explored for 100 epochs both in the absence and presence of noise; the findings, in this instance, are shown in Figure 11. The graph is a plot of the learning of the XG-Boost algorithm over 100 epochs in two conditions: (a) the noise-free condition and (b) with 20 dB of noise. In the latter condition (a) where no noise was present, the training and validation accuracies showed similar trend patterns of improvement, with the former reaching nearly perfect 0.95 and the latter leveling off at around 0.90. The training loss, which starts higher than 2.2, decreases significantly to around 0.2, while the validation loss also decreases from 1.0 to around 0.1, thereby indicating effective model learning and generalization.

5.2.3.1   Without noise   b) 20 dB noise

Figure 11: XG-Boost training performance

In contrast, with noise of less than 20dB (b), the model correctly classifies both the training and the validation data. However, the model has an ideal of around 78% accuracy for training and 68% for validation. The gap between the training and validation losses is huge, i.e. the training loss is about 1.2 in the beginning and then falls smoothly to 0.3 while the validation loss, though remaining steady at a high level, stays around 0.85–0.9, thus showing that the model still is not performing well on the noisy data. These results propose that the performance of XG-Boost is

great on the clean data, but its accuracy has dramatically cut down in the presence of the noise. CM for both noisy and non-noisy datasets can be seen in Figure 12.

**Figure 12:** CM of Light-GBM a) Without Noise b) 20 dB noise

5.3 Comparison Analysis

In this sub-section, comparisons of the current approach with each other and compared to the old approach are described in Tables 2 and 3 to reveal the position of the developed model. A comparative assessment of the proposed model is described in $A_{accuracy}$, $P_{precision}$, R_{recall}, and $F1_{score}$. The comparison shows that Ada-Boost performs best in terms of accuracy in both noise-free (99.92%) and noisy (99.86%) scenarios, with consistently high precision and recall. Light-GBM, while beginning with lower accuracy (95.65%), improves significantly under 20 dB noise (98.73%), which suggests good noise robustness. XG-Boost also improves with noise, from 96.46% to 98.64%. In general, Ada-Boost has the best accuracy and stability, and Light-GBM and XG-Boost have excellent robustness in noisy environments. Figure 13 illustrates the comparison graph of suggested models.

Table 2: Comparison of proposed three models

| Models		$A_{accuracy}$	$P_{precision}$	R_{recall}	$F1_{score}$
Ada-Boost	**Without Noise**	**99.92**	**99.17**	**99.44**	**95.89**
	20 dB Noise	**99.86**	**99.30**	**99.46**	**97.46**
Light-GBM	**Without Noise**	95.65	98.49	98.30	95.37
	20 dB Noise	98.73	97.84	98.31	96.64
XG-Boost	**Without Noise**	96.46	94.18	96.26	94.77
	20 dB Noise	98.64	96.27	97.61	95.37
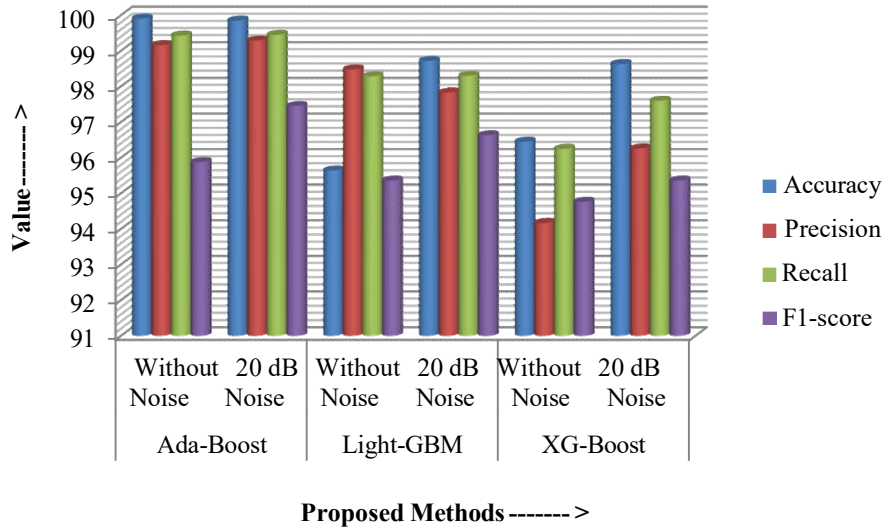
Figure 13: Comparison graph of proposed methods

Comparison of the proposed method with the literature is given in Table 3 to identify the position of the developed model. Fu et al. (2023) used a combination of Spatio-Temporal (ST) features and Convolutional Neural Networks (CNN) and achieved 99.12% accuracy without noise and a remarkable 99.80% with 20 dB noise, reflecting excellent performance in noisy conditions. For comparison, the suggested work based on the Ada-Boost algorithm performed better than all other algorithms in noise-free scenarios with 99.92% accuracy and performed strongly even with noise at 99.86%, proving both high accuracy and resilience. Figure 14 depicts the comparison graph of the proposed models with earlier models.

Table 3: Comparison of the proposed approach with the previous approach

Authors [Reference]	Methodology Used	Without Noise	20 dB Noise
		$A_{accuracy}$	
Fu et al., (2023) [34]	ST+CNN	99.12	99.80
Panigrahi et al., (2022) [35]	FDST+MFA_LGBM	99.71	96.85
Radhakrishnan et al., (2021) [36]	SE with (LR+NB+J48 DT)	91	95.60
Our Work	**Ada-Boost**	**99.92**	**99.86**
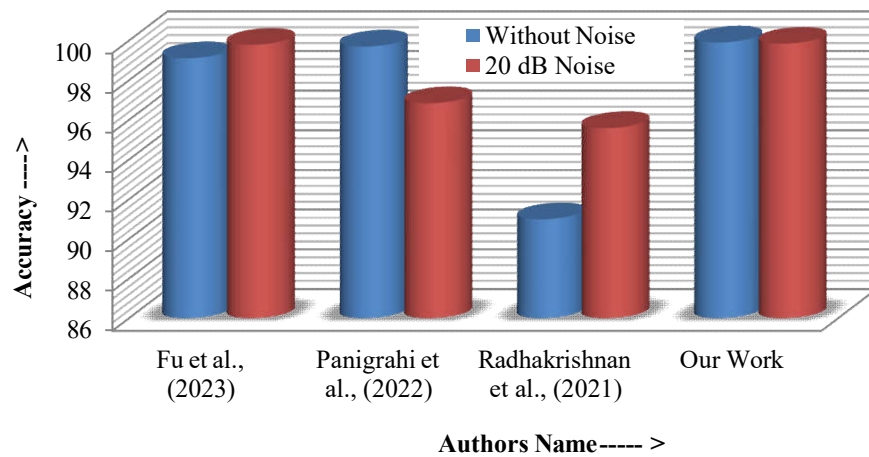
Figure 14: Comparison graph of proposed approach with the previous approach

6 Conclusion

PQ in modern power systems has become increasingly complex due to the integration of multiple energy sources, including conventional power plants and renewable resources like solar and wind. The aim of the research was to create an advanced model integrating different ML ensemble techniques, like "Ada-Boost, Light-GBM, and XG-Boost", for more accuracy in the power quality assessment in multi-source grid environments. Also, in the combined approach, the purpose was to solve the deficiencies in the old-fashioned techniques and individual ML models by achieving greater detection accuracy and the ability to work on noisy and complex signal data.

A synthetic PQD dataset was generated using an open-source tool in compliance with IEEE-1159, EN 50160, and IEC 61000 standards. The dataset included 16 types of PQDs with 500 samples per class, totaling 8000 signals. Noise levels of 20 dB and random variations were added to simulate real-world conditions. The Ada-Boost model performed better with a classification accuracy of 99.92% in noise-free conditions and 99.86% in 20 dB noise. Light-GBM was robust, particularly in noisy conditions, from 95.65% (noise-free) to 98.73% (noisy). XG-Boost performed fairly well, from 96.46% to 98.64% under noise.

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