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Research Paper

Automatic Fault Detection in Industrial Smart Grids Using KNN and Ensemble Classifiers

M. Venkata SUBBARAO[1a], G. Challa RAM[1b], D. Ramesh VARMA[1c], D. Girish KUMAR[1d], M. Prem KUMAR[1e]

[1]Department of ECE, Shri Vishnu Engineering College for Women, Bhimavaram, India
mandava.decs@gmail.com

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Abstract: The use of sensitive electrical gadgets in industries, buildings, smart cities, and homes has increased drastically in recent years. PQ events such as interruptions, surges, and sags have a high impact on these sensitive devices. The failure of these delicate devices in real-time applications, particularly smart applications, may result in significant damage. The supply quality decreases because of the failure of internal transmission system elements, unbalanced loads, and other outdoor issues such as weather. Several academics have proposed techniques to analyze these PQ disturbances, including wavelet packets, the S-transform, rough sets, and neural networks. In all the available algorithms, the classification procedure involves the extraction of a large set of features from the transformed outputs, training the classifier, and finally making a conclusion with the classifier. Because a large number of features are involved, the computational cost of all these methods increases. To reduce complexity and enhance classification efficiency, the proposed method focuses on extracting fewer low-complexity wavelet features from signals. In this study, pattern recognition (PR) methods, such as the wide variety of K-nearest neighbors (KNN) and ensemble classifiers, are used to classify PQ events. The performance of the proposed ML approaches is evaluated at various training and testing rates. Subsequently, the performance of the proposed strategies was compared to that of the current methods to determine the dominance of the proposed approaches.

Keywords: PQ disturbances, classification, KNN, Ensemble Classifiers, Wavelet features

1. Introduction

Recently, the use of delicate microelectronic appliances is rising. The presence of PQ disturbances can harm these gadgets easily. A PQ disturbance is defined as any variation in the power signals from their usual levels [1]. PQ disturbances are caused by rapid changes in the frequency and voltage of the clean sinusoidal waveforms [2]. Fault clearing, utility switching, and non-linear loads are the causes of these sudden changes. Such PQ fluctuations can trigger device failure, interrupting power transmission, and may cause failure of the entire grid network [3]. This subsection provides info on several existing methodologies and discusses the benefits and drawbacks of such approaches. Artificial Neural Networks (ANN), probabilistic neural network (PNN), and retrieved features by Discrete Wavelet Transform (DWT), Hilbert Transform (GT), and S-transform (ST) among others, are some of the existing methodologies. Ferhat Ucar [4] presented the W-ELM driven features extraction approach. further, ELM applied to classify the type of event. This approach yielded a 96% accurate categorization rate. Biawal [5] presented a Discrete ST based extraction of features and extracted 6 different features, and APSO and fuzzy C-means algorithms are implemented for PQ classification. This approach yielded a 96% accurate recognition rate. S. Mishra et al. [6] suggested an ST based feature selection technique and employed a PNN classifier to categories the PQ disturbance. This approach yielded a 96% accurate categorization rate.

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ORCID: [a]0000-0001-5840-2190; [b]0000-0002-3790-1318; [c]0000-0002-9517-4964; [d]0000-0002-2430-2834; [e]0000-0002-8702-8828

R. Bhavani and N. Rathina Prabha [7] presented feature extraction using Wavelet Packets and applied ANN for PQ noise classification. Among 200 actual events tested, this technique had a 95.25 percent successful classification rate. M. A. S. Masoum and colleagues [8] suggested a Wavelet Network Based Method for recognizing PQ events and the approach achieved a good recognition rate of 98.18 percent. Recently several new ML and deep learning-based approaches are proposed for classification of PQ disturbances. Decision trees (DT) are proposed with cumulant features for classification of 10 classes of PQ disturbances [9]. The performance of DT is superior but with course tree (CT) the max accuracy achieved is 71.64 %. Dawood Z et. al [10] proposed a PNN based architecture with artificial bee colony feature selection. The performance of the model used in [10] achieved accuracy of 64.65% to 99.98% at different iterations and features. However, the model is not achieved good accuracy at different iterations. Recently a new classification models are developed with ML and deep learning architectures such as SVM [11], Convolutional neural network (CNN) [12,13], DT [14], PNN [15], a CNN based hybrid DL approach [16], bidirectional GRU (Bi-GRU) [17] and adaptive chirp mode pursuit and grasshopper optimized SVM (ACMP + GOA + SVM) [18]. These approaches have superior classification than conventional approaches. However, most of the deep learning-based architectures suffered with the computational complexity and deep architectures for PQ classification.

The majority of current models consider only small set of disturbances into account. They examined analysis at a constant training rate of 80%. Furthermore, if they had introduced more classifications, there would be a risk of a loss in accuracy. The purpose of the study is to create a system that can categorize the PQ disturbances with a smaller number of features. So as to avoid these constraints, a number of combinations were evaluated and classified using KNN and Ensemble Classifiers.

The article is arranged as follows. The section 2 discusses WT decomposition and extraction of features. Section 3 describes the KNN and Ensemble Classifiers. Section 4 evaluates the effectiveness of KNN and Ensemble classifiers with various training rates. Finally, Section 5 presents the primary hypotheses of the research effort that have been derived through simulation.

2. Proposed Framework

Figure 1 represents the outline of the proposed PQ classifier. In first stage, different types of practical power quality event signals like Pure signal, Swell, Sag, Interruption, Impulsive transient, harmonics, flicker, Sag+harmonics, Swell+harmonics are collected using standard data bases. Signal Pre-processing is used to enhance data quality by resampling, eliminating outliers, and filling gaps from signal sets.

In feature extraction stage the data sets are applied to DWT (Meyer WT) to extract features from the signals. The extracted features are Mean energy, Shannon entropy, Max-percentage, and THD (total hormonic distortion). Further, the extracted features are fed to the ML classifiers for training.

ML provides the ability to the machine to learn the things based on the data provided and then it classifies the type of event based on the experience that it has gained in training phase. In this paper, 6 KNNs and 5 Ensemble classifiers are used as a PR classifier. The extracted datasets are divided into two parts. One part is for training the model and the second part is for testing the model by considering training rate as splitting criteria i.e.., 90%, 80%, 70%, 60%, 50% [9].

To demonstrate the superiority of the classifier, its performance is also evaluated at training rates of 50% and 60%. This analysis will show the dominance of the classifiers at lower training rates. In training phase, the model will try to draw patterns or insights from the data. In the testing phase, each model is evaluated at different testing rates like 10%, 20%, 30%, 40% and 50%.

Different performance metrics such as accuracy, Recall, Precision, Sensitivity, Specificity are evaluated to analyze the performance of the classifier.

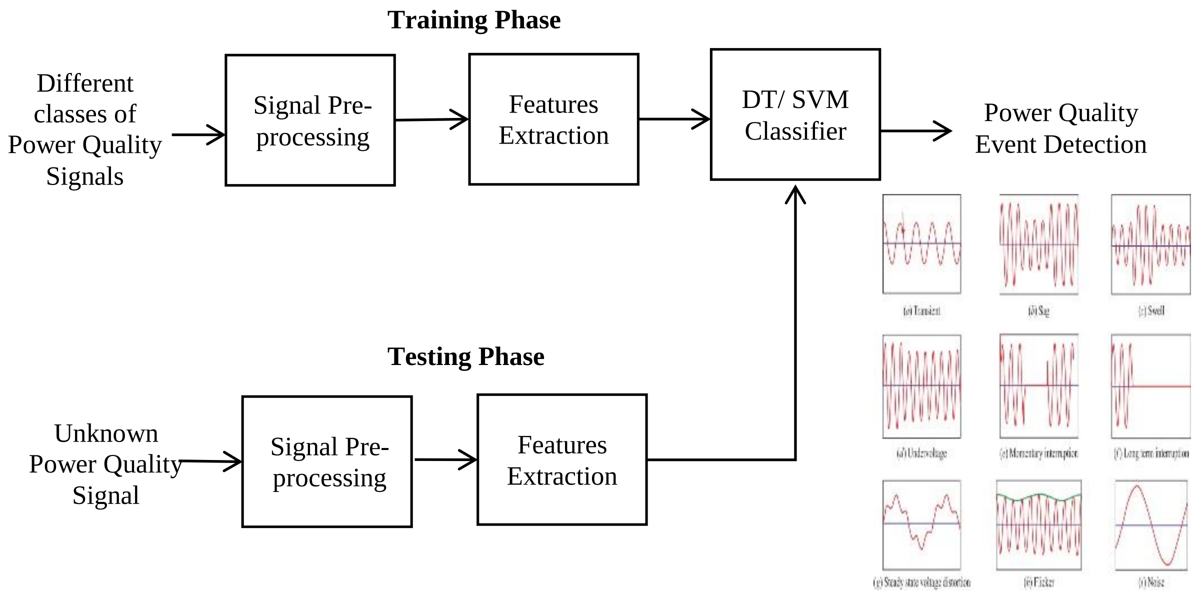

Figure 1. PQ Classifier Framework.

3. Methodology

KNN and Ensemble classifiers are chosen as a PR classifier for classification of PQ events. The basic principles of the proposed classifiers are as follows.

3.1. KNN Classifiers

The KNN is a supervised classifier suits for both binary and multi-class classification. These models are non-parametric. KNN classifier maintains all available instances and recognizes the new cases based on a similarity measure such as distance functions to identify a PQ signal. The signal is assigned to a PQ class in a KNN classifier based on a majority neighbours. The value of K is determined by the size of the data collection and determines the performance of the classifier. KNNs are classified into Cosine, Cubic, Fine, Medium, Coarse, and Weighted KNNs based on their K value and distance functions. Table 1 shows the features of each KNN. The suggested KNN classifier's performance is evaluated using various K values such as 1, 10, and 100, as well as various distance types such as Euclidian, cosine, and cubic distances. Weighted KNN makes a decision by computing a weighting function based on the Euclidian value.

By setting K=1, Fine KNN distinguishes between classes in minute detail. By K= 10 and 100, respectively, Medium KNN and Coarse KNN classifiers create fewer distinctions than Fine KNN. Cosine and Cubic KNN's uses cosine and cubic distances instead of Euclidean distance.

3.2. Ensemble Classifiers

Because of the methodological diversity of the classifiers, the PQ prediction accuracy of distinct PR classifiers varies across data sets. The optimum working categorization technique for multiple datasets cannot be predicted. To address this issue, ensemble learners are built using a diverse range of classifiers that can vote on decision making. These models can provide maximum prediction accuracy by majority of votes. When identifying a new entity, an ensemble classifier consists of a collection of independently trained models whose estimates are pooled. Boosting is the most often used ensemble strategy, and it works with the weighted training dataset.

Table 1. KNN Classifiers

Model	K	Distance Function	Distance (d)
Fine KNN	1	Euclidean	$\sqrt{\sum_{i=1}^{n}(p_i - q_i)^2}$
Medium KNN	10	Euclidean	$\sqrt{\sum_{i=1}^{n}(p_i - q_i)^2}$
Coarse KNN	100	Euclidean	$\sqrt{\sum_{i=1}^{n}(p_i - q_i)^2}$
Cosine KNN	10	Cosine	$\frac{\bar{P}.\bar{Q}}{\lvert\vec{P}\rvert\lvert\vec{Q}\rvert}$
Cubic KNN	10	Cubic	$\left(\sum_{i=1}^{m}\lvert p_i - q_i\rvert^3\right)^{1/3}$
Weighted KNN	10	Distance Weighting	$w = {}^{1}/_{d^2}$

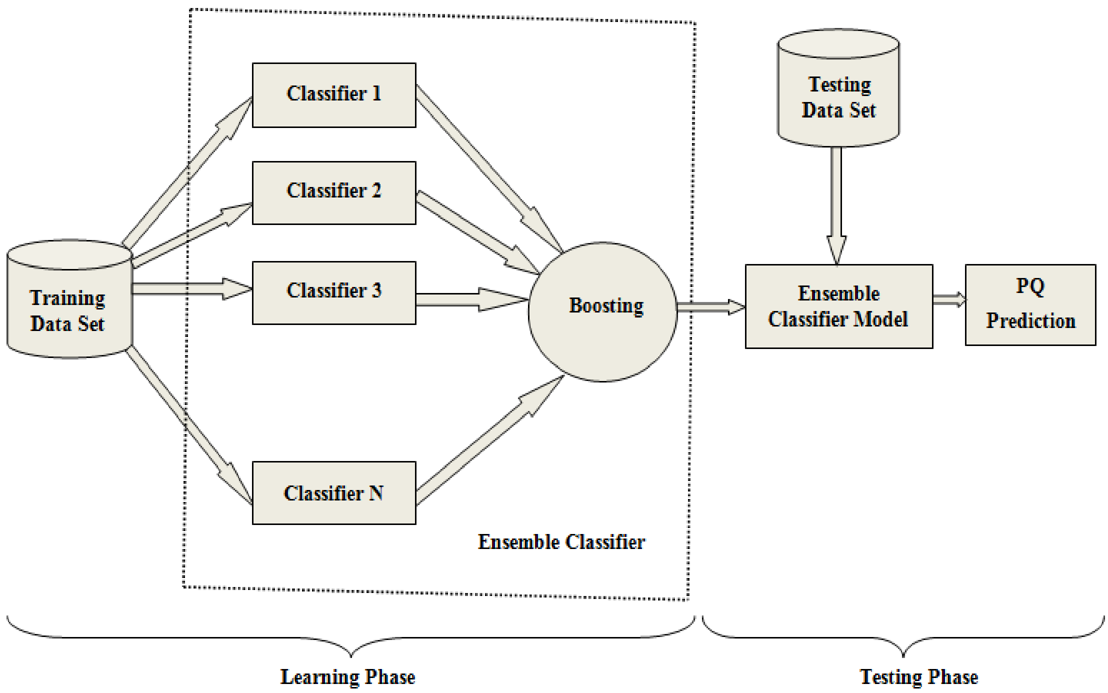

Figure 2. Ensemble Classifier

Boosting enhances the weights of poorly classified instances while lowering the weights of correctly predicted cases. As a result, instances that have been incorrectly predicted by past learners in the pool are picked more frequently than those that have been accurately classified. As an outcome, boosting helps in generating models for its ensemble that outperform the present ensemble performance. When the boosting process is finished, the ensemble classifier model is available for testing. The unseen testing data is applied to the ensemble classifier for PQ classification during the testing phase. Figure 2 depicts the detailed method of employing an ensemble classifier.

Five verity of ensemble methods are built for PQ identification, including bagged trees, boosted trees, RusBoosted trees, subspace discriminant KNN and subspace KNN in conjunction with the features provided in section 2. Deep trees are used to build bagged and boosted trees, which are slower in speed. subspace discriminant KNN and Subspace KNN on the other hand, make use of nearest neighbours and discriminant analysis. Weak learners in RusBoosted trees will be enhanced depending on arbitrary under sampling.

4. Results & Discussions

For simulations, three different data sets of PQ disturbances are considered. Dataset 1 consists of 1 lakh signals each class consists of 10000 signals. Dataset 2 consists of 5000 signals/class and Dataset 3 have 1000 signals/class. These data sets are considered as large, medium and small data sets in representations. Table 2 represents the parameters used in experiments.

Table 2. Parameters

Parameter	**Description**
PQ event	Swell, Sag, Pure signal, Interruption, Oscillatory transient, harmonics, Impulsive transient, Sag+harmonics, Swell+harmonics, and flicker.
Features	Mean energy, Shannon entropy, Max-percentage, Total harmonic distortion
Size of datasets	Dataset1 (10000 Signals/class), Dataset2 (5000 Signals/class), Dataset2 (1000 Signals/class)
Training rate	90%,80%,70%,60%,50%
Performance Measures	Accuracy, Recall, Precision, F1 Score and error rate
Classifiers	KNN, Ensemble classifiers

In order to know the performance of a classifier the following performance metrics are considered in this paper.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

$$\text{F1 Score} = \frac{2* \text{Precision} * \text{Recall}}{\text{Precision + Recall}} \tag{4}$$

$$\text{Error rate} = 100 - \text{percentage of Accuracy} \tag{5}$$

where TP, TN are true positive and negative rates. FP and FN are false positive and negative rates.

The confusion matrices of Fine KNN and Bagged trees at 90% training rate with dataset 1 is shown in Fig. 3 and 4 respectively and they achieved an accuracy of 98.4% and 98.5% respectively.

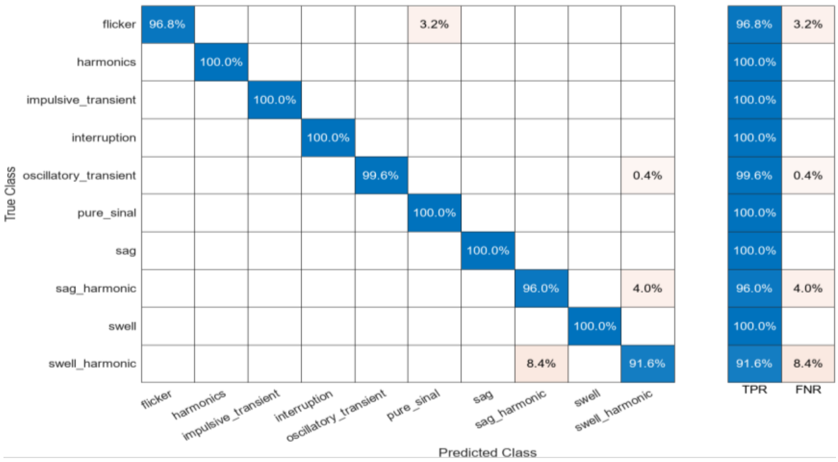

Figure 3. Confusion Matrix of Fine KNN at 90% training rate for Dataset1

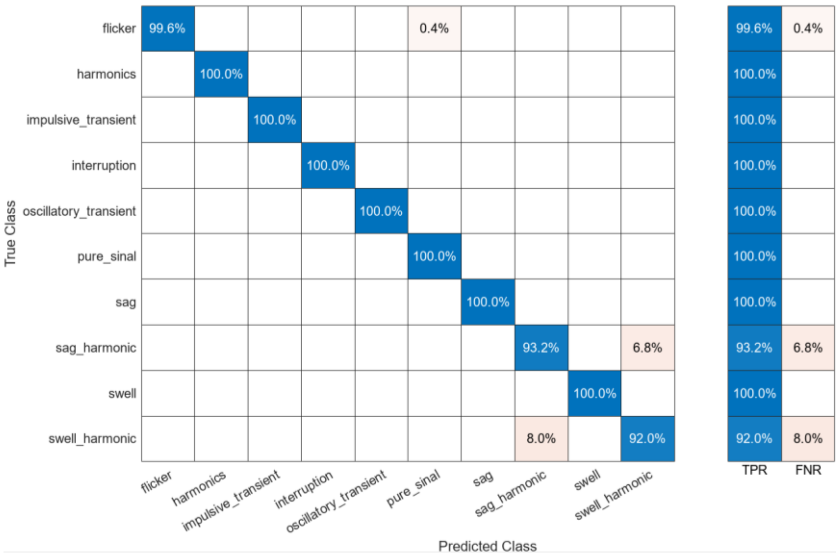

Figure 4. Confusion Matrix of Bagged Trees at 90% training rate for Dataset1

Table 3. Performance for Large Dataset (Dataset 1)

Model	Classifier	Training Rate %				
		90	80	70	60	50
KNN	Fine	98.4	97.5	97.7	97.6	97.6
	Medium	97.5	96.9	96.7	96.9	96.6
	Coarse	94.5	94	93.2	93.0	92.6
	Cosine	96.1	95.5	95.6	95.4	95.1
	Cubic	97.1	96.8	96.7	96.7	96.5
	Weighted	97.9	97.4	97.3	97.3	97.3
Ensemble	Boosted Tress	97.4	97	97	97.0	97.1
	Bagged Trees	98.5	98.2	98.4	98.3	98.2
	Subspace Discriminant	93.5	92.4	91.9	92.2	92.6
	Subspace KNN	98.1	97.4	97.9	97.6	97.5
	RUS Boosted Trees	96.7	96.7	96.1	96.3	96.5

Table 3 represents the performance of all models at various training and testing rates for large dataset. The highest accuracy of KNN Classifier is 98.4% for Fine KNN. The remaining KNN classifiers accuracy ranges from 92 to 97.9%. The highest accuracy of Ensemble Classifier is 98.5% for Bagged Tree. The remaining Ensembled classifiers accuracy ranges from 92 to 98.1%.
Table 4 represents the performance of all models at various training and testing rates for medium dataset. The highest accuracy of KNN Classifier is 98% for Fine KNN. The remaining KNN classifiers accuracy ranges from 87.2 to 97.8%. The highest accuracy of Ensembled Classifier is 98.1% for Bagged Tree. The remaining Ensembled classifiers accuracy ranges from 87.4% to 98%.

Table 4. Performance for Medium Dataset (Dataset 2)

Model	Classifier	Training Rate %				
		50	60	70	80	90
KNN	Fine	95.4	98	97.6	97.7	97.8
	Medium	93.4	96.9	96	96	96
	Coarse	87.2	91.6	91.7	91.1	91
	Cosine	91.6	91.4	94.9	95.2	94.7
	Cubic	93	92.5	95.5	97.9	95.7
	Weighted	94.4	97.6	97	97.5	97.1
Ensemble	Boosted Tress	93.4	97.1	97	97.3	97.4
	Bagged Trees	97.2	98	98	98	98.1
	Subspace Discriminant	87.4	92.7	92.7	92.8	92.7
	Subspace KNN	97	97.5	97.1	97.5	97.8
	RUS Boosted Trees	92.4	96.3	96.1	96.4	96.3

Table 5. Performance for Small Dataset (Dataset 3)

Model	Classifier	Training Rate %				
		50	60	70	80	90
KNN	Fine	93.5	95	97.7	98	98.4
	Medium	91	94	94.3	95	96
	Coarse	72	73	74	83	83.2
	Cosine	93.6	93.8	94	94.7	95
	Cubic	94.3	94.4	95	95.7	97
	Weighted	92	95.3	97	97.5	98
Ensemble	Boosted Tress	95.5	95.8	95.8	98.4	98.4
	Bagged Trees	95.7	95.9	96.4	97.8	98.5
	Subspace Discriminant	91	92.7	92.7	92.9	93.3
	Subspace KNN	92	95.5	96.3	97.5	97.8
	RUS Boosted Trees	94.8	95.3	95.3	96.4	96.5

Table 5 represents the performance of all models at various training and testing rates for small data set. The highest accuracy of KNN Classifier is 98.4% for Fine KNN. The remaining KNN classifiers accuracy ranges from 72% to 98%. The highest accuracy of Ensembled Classifier is 98.5% for Bagged Tree. The remaining Ensembled classifiers accuracy ranges from 91% to 98.4%.

Fig. 5, 6 and 7 represents the performance comparison of different KNN classifiers for Dataset 1, 2, and 3 respectively. From these figures it is observed that Fine KNN, Weighted KNN are the superior classifiers among all KNNs for PQ classification.

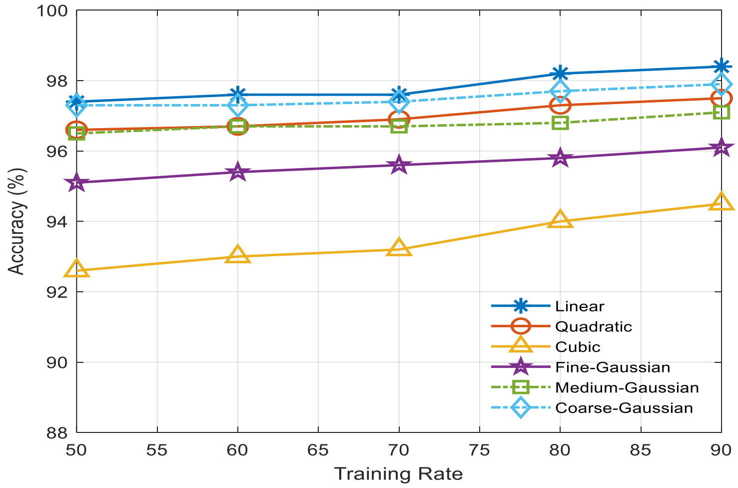

Figure 5. Performance comparision of KNN classifiers for Dataset 1

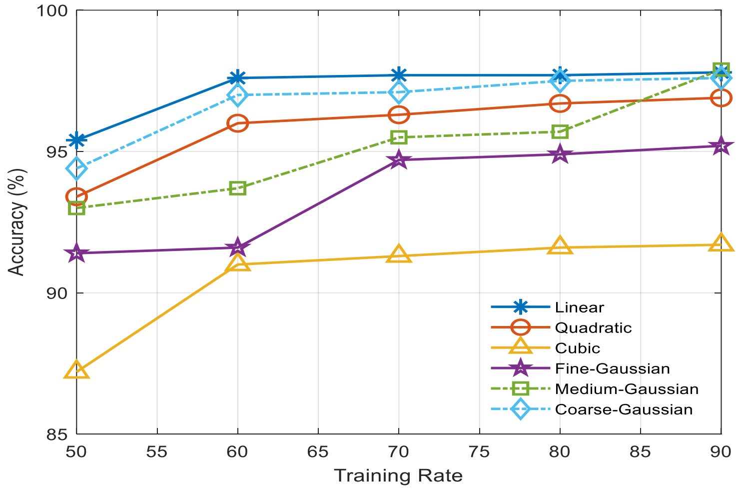

Figure 6. Performance comparision of KNN classifiers for Dataset 2

Table 6. Performance metrics of Fine KNN at 90% training rate (dataset 1)

PQ Class	Accuracy (%)	Precision (%)	Error Rate (%)	Recall (%)	F1 Score (%)
Flicker	96.8	100	3.2	96.8	98.4
harmonics	100	100	0	100	100
impulsive transient	100	100	0	100	100
interruption	100	100	0	100	100
oscillatory transient	99.6	100	0.4	99.6	99.8
pure sinusoidal	100	96.9	0	100	99.4
sag	100	100	0	100	98.4
sag harmonics	96	91.9	4	96	93.9
swell	100	100	0	100	100
swell harmonic	91	93	9	91	91.9

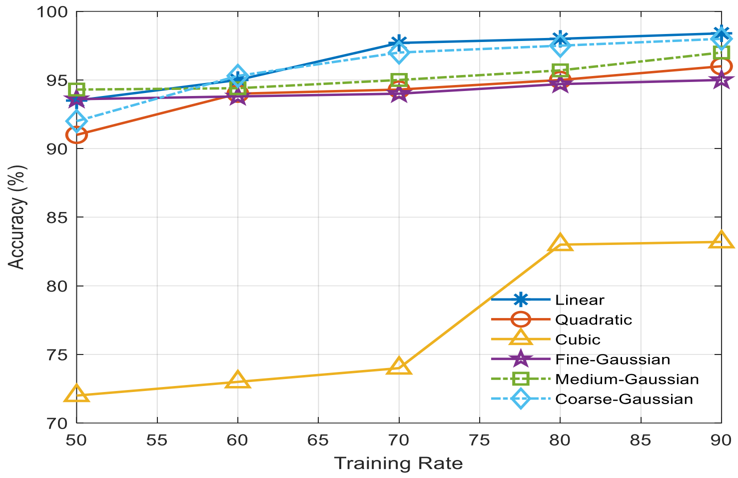

Figure 7. Performance comparision of KNN classifiers for Dataset 3

The performance metrics of Fine KNN and Weighted KNN at 90% training rate are shown in Table 6 and 7 respectively. Table 6 and 7 represents the performance metrics for each PQ class signals.

Table 7. Performance metrics of Weighted KNN at 90% training rate (dataset 1)

PQ Class	Accuracy (%)	Precision (%)	Error Rate (%)	Recall (%)	F1 Score (%)
Flicker	95	100	5	95	97.4
harmonics	100	99	0	100	99.4
impulsive transient	100	100	0	100	100
interruption	100	100	0	100	100
oscillatory transient	100	100	0	100	100
pure sinusoidal	100	95	0	100	97.4
sag	100	99	0	100	99.4
sag harmonics	92	93	7	92	92.4
swell	100	100	0	100	100
swell harmonic	92	92	8	92	92

Fig. 8, 9 and 10 represents the performance comparison of different Ensemble classifiers for Dataset 1, Dataset 2, and Dataset 3 respectively. From these figures it is observed that Boosted Trees and Bagged Trees are the superior classifiers among all Ensemble classifiers for PQ classification.

The performance metrics of Boosted Trees and Bagged Trees at 90% training rate are shown in Table 8 and 9 respectively. Table 8 and 9 represents the performance metrics for each PQ class signals.

Table 10 represents the performance comparison of proposed classifiers with other existing classifiers. However, some of the works proposed CNN based deep learning architectures [12,13,16,17] the accuracy is improved but the computational complexity and the number of layers in the network are very high.

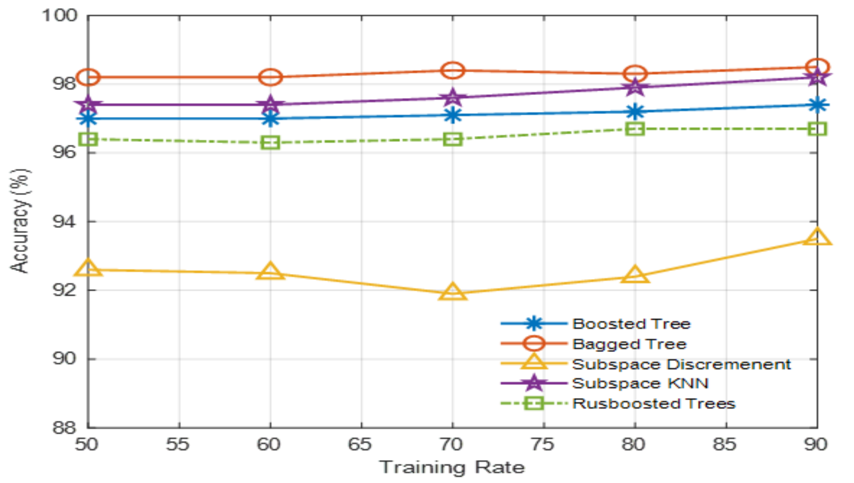

Figure 8. Performance comparision of Ensemble classifiers for Dataset 1

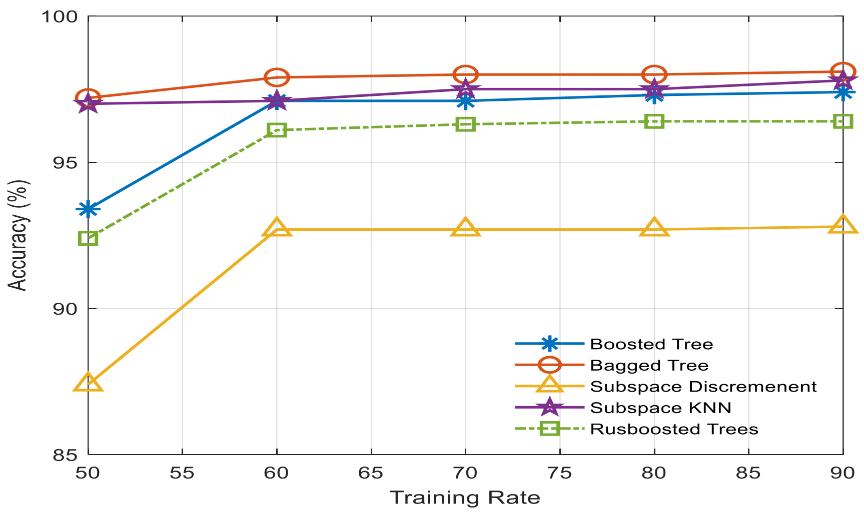

Figure 9. Performance comparision of Ensemble classifiers for Dataset 2

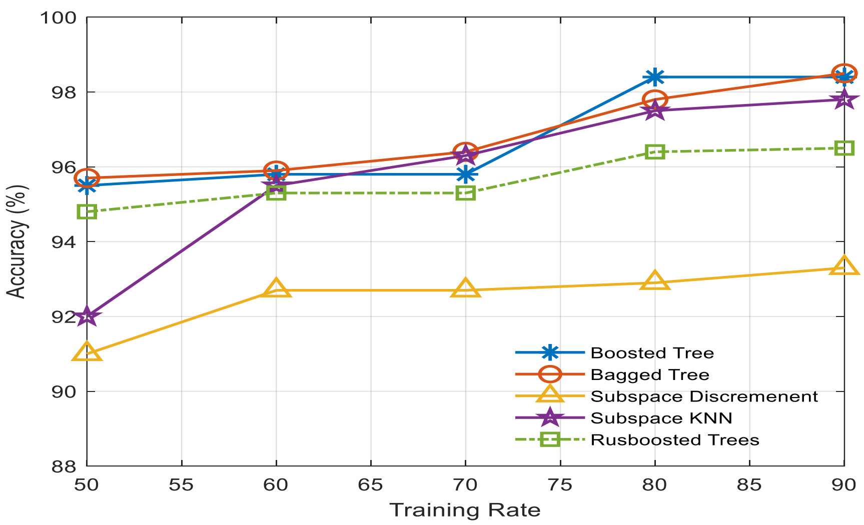

Figure 10. Performance comparision of Ensemble classifiers for Dataset 3

Table 8. Performance Analysis of Boosted Trees at 90% Training rate (dataset 1)

PQ Class	Accuracy (%)	Precision (%)	Error Rate (%)	Recall (%)	F1 Score (%)
Flicker	93	100	7	93	96.3
harmonics	100	100	0	100	100
impulsive transient	100	100	0	100	100
interruption	99	99	1	99	99
oscillatory transient	99	99	1	99	99
pure sinusoidal	100	94	0	100	96.9
sag	99	98	1	99	98.4
sag harmonics	95	88	5	95	91.3
swell	100	100	0	100	100
swell harmonic	89	94	11	89	91.4

Table 9. Performance Analysis of Bagged Trees at 90% Training rate (dataset 1)

PQ Class	Accuracy (%)	Precision (%)	Error Rate (%)	Recall (%)	F1 Score (%)
Flicker	99.6	100	0.4	99.6	99.8
harmonics	100	100	0	100	100
impulsive transient	100	100	0	100	100
interruption	100	99	0	100	99.4
oscillatory transient	100	100	0	100	100
pure sinusoidal	100	99.6	0	100	99.8
sag	100	100	0	100	100
sag harmonics	93.2	92.1	6.8	93.2	92.6
swell	100	100	0	100	100
swell harmonic	92	93.1	8	92	92.6

Table 10. Performance Comparison with other methods

Ref No.	Method	No. of Features	Accuracy (%)
[4]	W-ELM	4	98
[5]	ST, Fuzzy C-means & APSO	6	96.33
[6]	ST&PNN	7	96.10
[7]	WPT& ANN	7	95.25
[8]	DWT	8	98.18
[9]	DT - CT	3	71.64
[10]	PNN-adaptive AABC	9	64.65 - 99
[11]	SVM	-	87.28*
[12]	CNN	-	99.2*
[13]	CNN	-	98.13*
[14]	ST + FCM + DT	-	96.85*
[15]	WT + PNN + ABC	-	93.60*
[16]	hybrid deep learning (CNN)	-	97.54*
[17]	Bi-GRU	-	98*
[18]	ACMP + GOA + SVM	-	97.13*
Proposed	KNN Classifier Ensembled Classifier	6	98.4 98.5

*Performance at 20 dB SNR

Deep learning architectures required conversion of time domain signals in to time-frequency plots for the purpose of classification. From these simulations it is observed that the with six features, the proposed classifiers achieved better performance than the others with less computational complexity.

5. Conclusion

To categorize PQ disturbances, several KNN Classifiers and Ensembled Classifiers are developed in this paper. DWT has been used to extract six features from the data for training and testing. By taking into account the combination of disturbances, It is examined the performance of each model at various training rates ranging from 90% to 50% and testing rates ranging from 10% to 50%. As per the simulation findings, a maximum accuracy of 98.4 percent is obtained for Fine KNN and 98.5 percent for bagged trees, while the remaining classifiers accuracy varies from 94 percent to 98 percent for Dataset 1 and 100 percent for Dataset 3. It is also proved that the new approaches' accuracies outperform the existing approaches. Further, the accuracy can be improved by incorporating the feature selection algorithms along with ML classifiers and/or by applying deep learning architectures.

Authors' Contributions

M. Venkata Subbarao and G. Challa Ram developed the algorithms and the model. DRV and DGK have collected the datasets and performed the experimental analysis. MPR reviewed the existing approaches and performed a comparison analysis with the existing methods. MVS carried out the theoretical calculations in collaboration with GCR, DRV, DGK, and MPR and wrote up the article. M. Venkata Subbarao is the overall supervisor of the project.

All the authors read and approved the final manuscript.

Competing Interests

The authors declare that they have no competing interests.

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