International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2022): 7.942

Electrical Power Quality Classification using Nested Ensemble Learning

Supekar Unmesh Mahesh

School of Data Science, Symbiosis Skills and Professional University, Pune, India
Email: *unmeshsupekar3[at]gmail.com*
https://orcid.org/0000-0001-8134-2755

Abstract: ***With recent technological advancements, Machine learning (ML), and Deep learning (DL)is one of the most promising approaches used widely to correctly categorize diverse Power Quality events. In this paper, an effort is made to demonstrate the implementation and utilization of nested ensemble machine learning algorithms and hybrid ANN-Deep ConvNet(Artificial Neural Network-Deep Convolutional Neural Network). Ensemble machine learning classifiers used in the paper for Power Quality Event Classification are Decision Tree, Random Forest, K-NearestNeighbour(KNN), LightGradient Boosting Machine(LGBM), & AdaBoost. They are combined using a Stacking Classifier to perform Nested Ensemble Machine Learning Power Quality classification. The Research also proposes a Deep learning-based hybrid approach of Ensembled ANN-Deep ConvNet for accurate classification of Power Quality events.The confusion matrix and Accuracy table have been used as a measure of performance in the paper.***

Keywords: Electrical Power Quality; Ensemble Machine Learning; Ensemble learning; Deep Learning; Power Quality Classification; ANN-Deep ConvNet;

1. Introduction

India produces electricity at the third-largest global rate [1]. According to the Central Electricity Authority of India for FY 2020, Industrial and Residential Electricity consumption accounted for 42.69 % and 24.01 % respectively of the total electricity consumption of India [2]. With the new decade, Industry Tech giants planning to set up manufacturing facilities for semiconductor chips and Electric Vehicles in various parts of India,Power electronic parts are being used in hardware more frequently[3]. Therefore, it is vital to assess the integrity and quality of the power being used.There are various power quality events such as Overvoltage, Undervoltage, Voltage Swell, Voltage Sag, Voltage Spike, Flicker, Voltage Interruptions, Harmonic Distortions, etc. Correct and timely identification of poor power quality can protect consumers and users against huge losses.The Power Quality Analysis is often misassociated with the Voltage Quality. Technically Electrical Power is the product of Voltage and Current. In reality, it is the Voltage and the Current both are responsible for the Electrical Power Quality. The Power Generators may generate a Pure Sinusoidal Voltage supply but the Current associated with the power system may lead to the creation of Power Quality Events and abnormalities in the supply. The Current in the power system depends on the connected load on the consumer side hence Power Quality is often a term on the Consumer side. Fig. 1a & 1b show perceptions of causes for Power Quality Events.

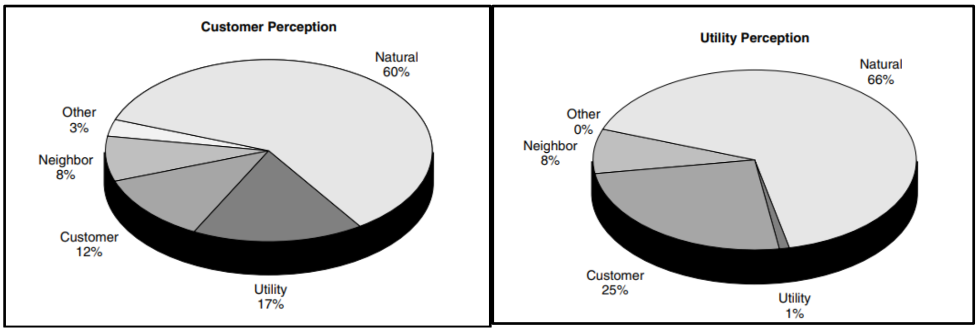

Figure 1a & 1b: Perceptions of Causes for Power Quality Events.[4]

2. Related Work

To address power quality issues, the automatic classification of Power quality event occurrences is crucial, [5] proposes an ensemble deep learning framework to realize intelligent classification of PQ disturbances based on the characteristics of the sequence of disturbance signals, the Long Short Term Memory (LSTM) network was used to classify the signals the Bagging theory was used to integrate the training results of multiple LSTM networks to improve the generalization of the network [5]. There are multiple ways to generate data for power quality events, In[6] an Open source dataset generator isproposed which synthetically generates the data based on MATLAB software this enables multiple researchers to get to a common ground of data source for easier comparison [6]. Another research group proposed a hybrid approach of CNN-LSTM(Convolutional Neural Network-Long Short Term Memory) in the paper [7]. Initially, the first two CNN layers are used to learn spatial data, and then a recurrent LSTM layer is used to learn the temporal properties followed by a dense layer with a softmax activation function, the features produced by the max-pooling layer of the CNN(Convolutional Neural Network) are passed to the LSTM layer [7].

The authors of [8] describe various applications and deep learning algorithms for the power quality classification community to introduce to them various deep learning algorithms their functionalities and possible applications in the Power quality classification[8]. The paper also introduces Big data and concepts related to Big data to the readers and attempts to familiarize the readers with Artificial Intelligence and convinces them of the use of these Intelligent methods over traditional ways [8]. The modeling and simulation of Power quality disturbances have always been an alternative opted for by many researchers to generate data in the first place while performing power quality classification, [9] describes simulation and modeling techniques for the generation of Power quality events based on their parametric equations [9].

The paper [10] shows the comparison of CNN, and LSTM forthe classification of Power Quality disturbance of sag, swell, harmonics,transient, notch & interruption on the current and voltage time data generated from MATLAB Simulink with an accuracy of 83.66%[10]. In the paper [11]Discrete Wavelet Transform is used along with Artificial Neural Networks to classify 20 types of power quality disturbances with the highest accuracy of 91.27 %, This method of feature extraction results in frequency and time domain of features and is also one of the applied methods for feature extraction [11]. An approach similar to the applied approach in this paper is shared in [12] which uses Nested Ensemble Machine learners for churn prediction in the telecom industry [12] has applied the Nested Ensemble learners combined namely K-Nearest Neighbor(KNN), Artificial Neural Network (ANN), Decision Tree, Naïve Bayes, Logistic Regression on multiple datasets to test the performance [12].Another group of researchers in their paper use Ensemble learning algorithms of Gradient boosting machines, Xgboost, Catboost, and Adaboost for remote sensing applications[13]. In [14]multiple signal processing methods are discussed to give various alternatives for feature extraction of Power Quality classification like wavelet transform, Fourier transforms, fast Fourier transform,short-term Fourier transform, etc[14]. In [15] the authors use forward selection, backward elimination, forward stepwise selection, backward stepwise elimination & random mutation for feature selection, and Least square-support vector machines for classifying 6 electrical power events with an overall accuracy of 98.88% [15]. Fig. 2 Shows various power quality events and their specifications. The Figure shows specifications in terms of voltage magnitude.

Categories	Typical spectral content	Typical duration	Typical voltage magnitude
1.0 Transients			
1.1 Impulsive			
1.1.1 Nanosecond	5-ns rise	<50 ns	
1.1.2 Microsecond	1-µs rise	50 ns–1 ms	
1.1.3 Millisecond	0.1-ms rise	>1 ms	
1.2 Oscillatory			
1.2.1 Low frequency	<5 kHz	0.3–50 ms	0–4 pu
1.2.2 Medium frequency	5–500 kHz	20 µs	0–8 pu
1.2.3 High frequency	0.5–5 MHz	5 µs	0–4 pu
2.0 Short-duration variations			
2.1 Instantaneous			
2.1.1 Interruption		0.5–30 cycles	<0.1 pu
2.1.2 Sag (dip)		0.5–30 cycles	0.1–0.9 pu
2.1.3 Swell		0.5–30 cycles	1.1–1.8 pu
2.2 Momentary			
2.2.1 Interruption		30 cycles–3 s	<0.1 pu
2.2.2 Sag (dip)		30 cycles–3 s	0.1–0.9 pu
2.2.3 Swell		30 cycles–3 s	1.1–1.4 pu
2.3 Temporary			
2.3.1 Interruption		3 s–1 min	<0.1 pu
2.3.2 Sag (dip)		3 s–1 min	0.1–0.9 pu
2.3.3 Swell		3 s–1 min	1.1–1.2 pu
3.0 Long-duration variations			
3.1 Interruption, sustained		>1 min	0.0 pu
3.2 Undervoltages		>1 min	0.8–0.9 pu
3.3 Overvoltages		>1 min	1.1–1.2 pu
4.0 Voltage unbalance		Steady state	0.5–2%
5.0 Waveform distortion			
5.1 DC offset		Steady state	0–0.1%
5.2 Harmonics	0–100th harmonic	Steady state	0–20%
5.3 Interharmonics	0–6 kHz	Steady state	0–2%
5.4 Notching		Steady state	
5.5 Noise	Broadband	Steady state	0–1%
6.0 Voltage fluctuations	<25 Hz	Intermittent	0.1–7% 0.2–2 Pst
7.0 Power frequency variations		<10 s	

NOTE: s = second, ns = nanosecond, µs = microsecond, ms = millisecond, kHz = kilohertz, MHz = megahertz, min = minute, pu = per unit.

Figure 2: Power Quality Events and their Specifications [4].

3. Proposed Work

3.1. Methodology

The paper discusses a study of Ensembled Machine Learning and Ensembled Deep Learning methods. The paper uses Bagging, Boosting, &Machine Learning(ML) classification algorithms in association with Stacking Ensemble Learning for Machine learning classifiers andArtificial Neural Network-Deep Convolutional Neural Network (ANN-DCNN) Stacking Ensemble Deep Learning for the classification of Power Quality Disturbances. The ML method proposed in this paper utilizes 5 Machine learning classifiers and Ensemble machine learning classifiers. The Classifiers used in the paper are Decision Tree, Random Forest, KNN, AdaBoost Classifier, and LGBM Classifier[16]. The classifiers are stacked together. The Data is imported and parallelly processed in the ML classifiers. The Ensemble learning technique is used to combine the strengths of various ML and ensemble classifiers to overcome individual drawbacks and shortcomings, hence improving accuracy[17]. Fig. 3 shows a Block diagram of the proposed methodology.Stacking decision trees, random forests, light gradient boosting machines, and Adaboost together can be a powerful combination for predictive modeling. Each of these algorithms has its strengths and weaknesses, and combining them can help to create a more robust model[18]. Decision trees are easy to interpret and can be used to create complex models. Random forests are an ensemble method that combines multiple decision trees to create a more robust model. They are less prone to overfitting and can handle larger datasets. Light gradient boosting machines are a type of boosting algorithm that uses decision trees as its base learners [19]. They are powerful and can be used to create complex models. Adaboost is another type of boosting algorithm that uses decision trees as its base learners. By combining these four algorithms, you can create a more robust model that is less prone to overfitting and can handle larger datasets [20]. Additionally, you can use the strengths of each algorithm to create a more accurate model. For example, you can use the interpretability of decision trees, the robustness of random forests, the power of light gradient boosting machines, and the efficiency of Adaboost to create an accurate and interpretable model [12].

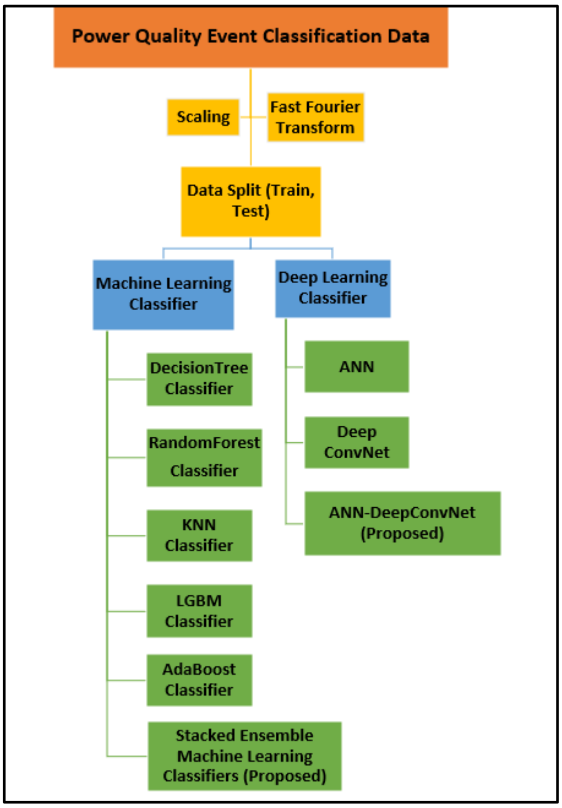

Figure 3: Block diagram of the proposed methodology

3.1.1. Stacking Ensemble Machine Learning Classifiers:

Stacking ensemble classifiers is a powerful machine-learning technique that combines multiple classifiers to create a more accurate and robust model[21]. Fig. 4 shows Stacking the Ensemble & Machine learning (ML) classifiers of the Nested Ensemble Machine Learning Model Stacking is a powerful technique because it allows the model to learn from the strengths of multiple classifiers. By combining the predictions of multiple classifiers, the model can learn from the strengths of each classifier and make more accurate predictions. This is especially useful when the base learners are not very accurate on their own. Stacking can also be used to reduce the variance of the model[22]. By combining the predictions of multiple classifiers, the model can reduce the variance of the predictions and make more accurate predictions[21].

```
StackingClassifier(estimators=[('dtc', DecisionTreeClassifier()),
                               ('rfc', RandomForestClassifier()),
                               ('knn', KNeighborsClassifier()),
                               ('lgbtq', LGBMClassifier()),
                               ('abc',
                                AdaBoostClassifier(learning_rate=0.17,
                                                   random_state=0))],
                   final_estimator=LogisticRegression())
```

Figure 4: Stacking the Ensemble & Machine learning classifiers of the Nested Ensemble Machine Learning Model

3.1.2. Stacking Deep Learning Networks- Ensemble Learning:

Stacked ANN-DCNN (Artificial Neural Network-Deep Convolutional Neural Network) is a type of deep learning architecture that combines the strengths of both ANNs (Artificial Neural Networks) and DCNNs (Deep Convolutional Neural Networks). The stacked ANN-DCNN architecture consists of two layers: an ANN and a DCNN. Fig. 5a shows ANN &Fig. 5b shows The Deep CNN Model of the ANN-Deep ConvNet model.The ANN is responsible for learning the non-linear relationships between the input and output variables, while the CNN is responsible and has its strength for recognizing patterns in the input data[23]. These two are connected in a way that allows the ANN to pass information to the DCNN layer, which then uses the information to make predictions. The stacked ANN-DCNN architecture has several advantages over traditional ANNs and CNNs[24]. It is more efficient as it requires fewer parameters and computations, it is more accurate, and it is more robust than traditional ANNs and CNNs.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape
=================================================================
 dense (Dense)               (None, 100)

 dense_1 (Dense)             (None, 6)

=================================================================
Total params: 26,306
Trainable params: 26,306
Non-trainable params: 0
```

```
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d (Conv1D)             (None, 256, 128)          512

 batch_normalization (BatchN  (None, 256, 128)         512
 ormalization)

 max_pooling1d (MaxPooling1D  (None, 128, 128)         0
 )

 conv1d_1 (Conv1D)           (None, 128, 128)          49280

 conv1d_2 (Conv1D)           (None, 128, 128)          49280

 batch_normalization_1 (Batc  (None, 128, 128)         512
 hNormalization)

 max_pooling1d_1 (MaxPooling  (None, 64, 128)          0
 1D)

 flatten (Flatten)           (None, 8192)              0

 dense_2 (Dense)             (None, 16)                131088

 dropout (Dropout)           (None, 16)                0

 dense_3 (Dense)             (None, 6)                 102
```

Figure 5a & 5b: ANN & The Deep CNN Model of ANN-Deep ConvNet model

3.1.3. The Data:

There are multiple ways to perform Power Quality Event classification. Fig.6 shows Power Quality Classification types based on the type of data.

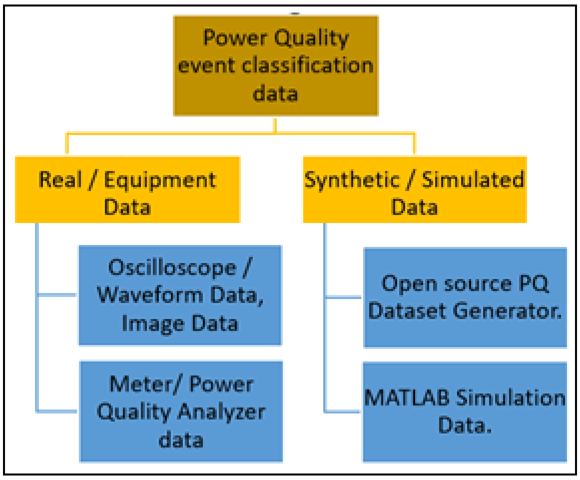

Figure 6: Power Quality Event classification based on the type of data.

The Dataset used can be publicly accessed throughthe GitHub link 'https://github.com/unmeshsupekar3/pqdataset'[25]. The dataset consists of 6000 samples of signals each signal characterized by 257 data points. Signals are categorized into 6 classes symbolizing Power Quality Events. The Power Quality Events addressed by the Dataset are Voltage Sag, Voltage Swell, Notches, Transients, and Harmonics.

4. Results and Analysis

4.1. The ML Nested Ensemble learning models

The ML Nested Ensemble learning models were tested and evaluated for their performance under various conditions of varying Noise levels. Gaussian Noise was added to the data at various dB levels and conditions as No Noise, 5 dB, 20 dB, 30dB, 40 dB, & 50dB, and the consolidated results are shown in Table 2 for ML Nested Ensemble learning model performance.Table 1 shows the Confusion Matrix for the StackingClassifier of the Nested Ensemble Machine Learning Model. The matrix is a 6x6 matrix representing 6 classes from the power quality dataset. The Nested Ensemble Machine Learning Model achieves a Maximum overall accuracy of 0.9983 on the Dataset.

Table 1: Confusion Matrix and class target predictions for the Nested Ensemble Machine Learning Model.

Confusion Matrix for the Nested Ensemble Machine Learning Model.					
263	0	0	0	0	0
0	293	0	0	0	0
5	0	325	0	0	0
0	0	0	299	0	0
0	0	0	0	309	0
0	0	0	0	0	306

Table 2: Performance of Nested Ensemble Machine learning classifier model.

Classifier		Accuracy					
		No noise	5 dB	20dB	30dB	40dB	50dB
DecisionTreeClassifier()		0.9909	0.9921	0.9907	0.9911	0.9904	0.9864
RandomForestClassifier()		0.9971	0.9985	0.9983	0.9978	0.9971	0.9973
KNeighborsClassifier()		0.9971	0.9966	0.9980	0.9973	0.9973	0.9969
LGBMClassifier()		0.9976	0.9985	0.9980	0.9971	0.9976	0.9969
AdaBoostClassifier()		0.9945	0.9961	0.9790	0.9790	0.9954	0.9804
StackingClassifier	Maximum	0.9992	0.9985	0.9992	1.0000	0.9985	0.9985
	Average	0.9973	0.9976	0.9988	0.9985	0.9983	0.9973

4.2. The ANN-DeepConvNet model

The ANN-ConvNet model was tested and evaluated for their performance under various conditions Gaussian Noise was added to the data at various dB levels and conditions as No Noise, 5 dB, 20 dB, 30dB, 40 dB, & 50dB, and the consolidated results are shown in Table 4 for the ANN-ConvNet model performance.Table 3 shows the Confusion Matrix for the ANN-ConvNet model. The matrix is a 6x6 matrix representing 6 classes from the power quality dataset.

The ANN-DeepConvNet model achieves a Maximum accuracy of 0.9983 on the Dataset.

Table 3: Confusion Matrix for ANN-Deep ConvNet Model

Confusion Matrix for ANN-Deep ConvNet Model					
266	0	0	0	0	0
0	286	0	0	0	0
7	0	311	0	0	0
0	0	0	328	0	0
0	0	0	0	302	0
0	0	0	0	0	300

Table 4: Performance of ANN-Deep ConvNet Ensemble learning model

Model		Accuracy					
		No Noise	5 dB	20 dB	30 dB	40 dB	50dB
ANN		0.9983	0.9972	0.9988	0.9972	0.9950	0.9966
DCNN		0.9983	0.9978	0.9938	0.9983	0.9944	0.9966
Ensembled ANN-DCNN	Maximum	0.9983	0.9978	0.9988	0.9983	0.9950	0.9966
	Average	0.9983	0.9975	0.9963	0.9977	0.9947	0.9966

Fig. 7a shows the Accuracy and Error plot of the ANN model of the ANN-Deep ConvNet&Fig. 7b shows the Deep ConvNetmodel used for Power Quality Event Classification. The total number of epochs used for the ANN model was 5 epochs and for the Deep CNN model was 12 epochs.

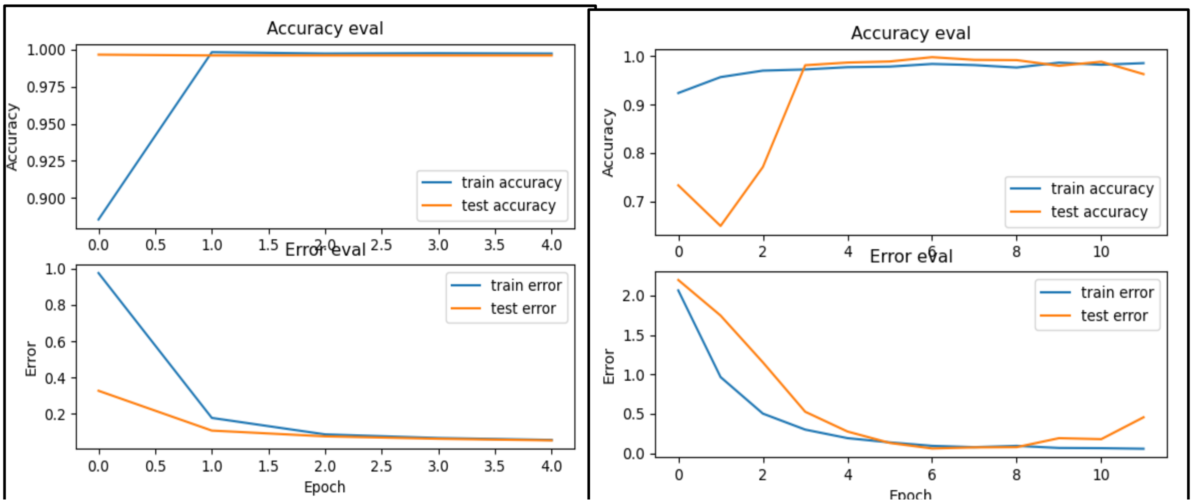

Figure 7a & 7b: Accuracy and Error Plot of ANN model of ANN-Deep ConvNet model

5. Conclusion

In this paper, the Nested Ensemble Machine Learning Model and ANN-Deep ConvNet Model are proposed and evaluated to perform the Power Quality Event Classification. The Proposed models are compared with the existing alternative approaches and models and were found to perform better under Normal No Noise and various Noise Conditions in the signal than others. The Models were also compared for their performance with individual weak learner Classifiers as in Table 2 and Table 4. The individual classifier accuracy acts asthe base Benchmark accuracy for the dataset. It was hence found that Ensemble classifiers and Machine Learning Classifiers can perform better when Stacked together and hence the name Nested Ensemble Machine Learning Model. It was also observed that the overall classifier accuracy was improved when the classifiers are Unified. The ANN- Deep ConvNet model is a hybrid ensemble learning model proposed in this paper that uses the strength of both the ANN and Deep ConvNet and when used unitedly displays an improved performance and accuracy in Power Quality Events Classification.

6. Future Scope

The real-time & high precision identification and classification of Power Quality Events is a wide domain for future research. The Research proposed in this paper has a scope to widen its horizons in multiple dimensions such as prototyping and deployment of the models proposed in the paper using Raspberry Pi, improvement in reducing classification delay, taking into consideration of Joint impact and occurrence of Power Quality Events. The futuristic Artificial Intelligence models can also be developed to handle Power Quality Event data from multiple sources, correctly identify them, & also mitigate them with necessary measures.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] bp, "Full report – Statistical Review of World Energy 2021".

[2] "GROWTH OF ELECTRICITY SECTOR IN INDIA FROM 1947-2020 GOVERNMENT OF INDIA MINISTRY OF POWER CENTRAL ELECTRICITY AUTHORITY NEW DELHI".

[3] "vedanta: Foxconn, Vedanta plan tech tie-up with STM for India semiconductor manufacturing unit - The Economic Times." https://economictimes.indiatimes.com/tech/technology/foxconn-vedanta-eye-stm-as-tech-partner/articleshow/97587009.cms (accessed Feb. 19, 2023).

[4] "Electrical Power Systems Quality, Second Edition." J. Wang, D. Zhang, and Y. Zhou, "Ensemble deep learning for automated classification of power quality disturbances signals," *Electric Power Systems Research*, vol. 213, Dec. 2022, doi: 10.1016/j.epsr.2022.108695.

[5] R. Machlev, A. Chachkes, J. Belikov, Y. Beck, and Y. Levron, "Open Source Dataset Generator for Power Quality Disturbances with Deep-Learning Reference Classifiers."

[6] *2017 International Conference on Technological Advancements in Power and Energy (TAP Energy).* IEEE, 2017.

[7] R. A. de Oliveira and M. H. J. Bollen, "Deep learning for power quality," *Electric Power Systems Research*, vol. 214. Elsevier Ltd, Jan. 01, 2023. doi: 10.1016/j.epsr.2022.108887.

[8] IEEE Power Electronics Society, Institute of Electrical and Electronics Engineers, UniversitiTeknologi Malaysia, IEEE Malaysia Section. Power Electronics Chapter, and ChŏllyŏkChonjaHakhoe, *2014 IEEE*

Conference on Energy Conversion (CENCON) : 13-14 October 2014, Johor Bahru, Malaysia.

[9] C. I. Garcia, F. Grasso, A. Luchetta, M. C. Piccirilli, L. Paolucci, and G. Talluri, "A comparison of power quality disturbance detection and classification methods using CNN, LSTM and CNN-LSTM," *Applied Sciences (Switzerland)*, vol. 10, no. 19, pp. 1–22, Oct. 2020, doi: 10.3390/app10196755.

[10] Staffordshire University and Institute of Electrical and Electronics Engineers, *Evaluation and Classification of Power Quality Disturbances Based on Discrete Wavelet Transform and Artificial Neural Networks*.

[11] M. Ahmed, H. Afzal, I. Siddiqi, M. F. Amjad, and K. Khurshid, "Exploring nested ensemble learners using overproduction and choose approach for churn prediction in telecom industry," *Neural Comput Appl*, vol. 32, no. 8, pp. 3237–3251, Apr. 2020, doi: 10.1007/s00521-018-3678-8.

[12] Y. Zhang, J. Liu, and W. Shen, "A Review of Ensemble Learning Algorithms Used in Remote Sensing Applications," *Applied Sciences (Switzerland)*, vol. 12, no. 17. MDPI, Sep. 01, 2022. doi: 10.3390/app12178654.

[13] S. Khokhar, A. A. B. Mohd Zin, A. S. B. Mokhtar, and M. Pesaran, "A comprehensive overview on signal processing and artificial intelligence techniques applications in classification of power quality disturbances," *Renewable and Sustainable Energy Reviews*, vol. 51. Elsevier Ltd, pp. 1650–1663, Aug. 07, 2015. doi: 10.1016/j.rser.2015.07.068.

[14] H. Erişti, Ö. Yildirim, B. Erişti, and Y. Demir, "Optimal feature selection for classification of the power quality events using wavelet transform and least squares support vector machines," *International Journal of Electrical Power and Energy Systems*, vol. 49, no. 1, pp. 95–103, 2013, doi: 10.1016/j.ijepes.2012.12.018.

[15] P. Biswas and T. Samanta, "Anomaly detection using ensemble random forest in wireless sensor network," *International Journal of Information Technology (Singapore)*, vol. 13, no. 5, pp. 2043–2052, Oct. 2021, doi: 10.1007/s41870-021-00717-8.

[16] N. Sharma, M. Mangla, S. N. Mohanty, and C. R. Pattanaik, "Employing stacked ensemble approach for time series forecasting," *International Journal of Information Technology (Singapore)*, vol. 13, no. 5, pp. 2075–2080, Oct. 2021, doi: 10.1007/s41870-021-00765-0.

[17] R. Ahuja and S. C. Sharma, "Stacking and voting ensemble methods fusion to evaluate instructor performance in higher education," *International Journal of Information Technology (Singapore)*, vol. 13, no. 5, pp. 1721–1731, Oct. 2021, doi: 10.1007/s41870-021-00729-4.

[18] S. Shastri, P. Kour, S. Kumar, K. Singh, and V. Mansotra, "GBoost: A novel Grading-AdaBoost ensemble approach for automatic identification of erythemato-squamous disease," *International Journal of Information Technology (Singapore)*, vol. 13, no. 3, pp. 959–971, Jun. 2021, doi: 10.1007/s41870-020-00589-4.

[19] S. Shastri, P. Kour, S. Kumar, K. Singh, A. Sharma, and V. Mansotra, "A nested stacking ensemble model for predicting districts with high and low maternal mortality ratio (MMR) in India," *International Journal of Information Technology (Singapore)*, vol. 13, no. 2, pp. 433–446, Apr. 2021, doi: 10.1007/S41870-020-00560-3/METRICS.

[20] "Stacking in Machine Learning - Javatpoint." https://www.javatpoint.com/stacking-in-machine-learning (accessed Feb. 27, 2023).

[21] H. N. Abdoli, A. J. Bidgoly, and S. Fallah, "Intrusion detection system using soft labeling and stacking ensemble," *International Journal of Information Technology (Singapore)*, vol. 14, no. 7, pp. 3711–3718, Dec. 2022, doi: 10.1007/S41870-022-01114-5/METRICS.

[22] S. Sachar and A. Kumar, "Deep ensemble learning for automatic medicinal leaf identification," *International Journal of Information Technology (Singapore)*, vol. 14, no. 6, pp. 3089–3097, Oct. 2022, doi: 10.1007/s41870-022-01055-z.

[23] M. Vijayalakshmi and V. J. Peter, "CNN based approach for identifying banana species from fruits," *International Journal of Information Technology (Singapore)*, vol. 13, no. 1, pp. 27–32, Feb. 2021, doi: 10.1007/s41870-020-00554-1.

[24] "unmeshsupekar3/pqdataset." https://github.com/unmeshsupekar3/pqdataset (accessed Feb. 24, 2023).