International Journal Of Innovative Trends In Multi Disciplinary Scientific Research
ISSN (Online): 3139 – 2687
(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

Development of real - time power quality monitoring and analysis system using IoT and big data analytics.

Shaikh Nagma Anis[1], Prof.Miss Alfiya A. Mahat[2]

1PG Scholar, Department of Electrical Engineering (Electrical Power System), MSS's College of Engineering and Technology, Jalna

[2]Assistant Professor, Department of Electrical Engineering, MSS's College of Engineering and Technology, Jalna

(Affiliated to Dr. Babasaheb Ambedkar Technological University, Lonere, Maharashtra)

Abstract

The increasing use of sensitive electronic equipment and nonlinear loads has made power quality monitoring an important requirement in modern electrical systems. Disturbances such as voltage sag, swell, harmonics, flicker, and interruptions can significantly affect system performance, reduce equipment lifespan, and increase operational losses. This paper presents an IoT-based real-time power quality monitoring and analysis system integrated with big data analytics and deep learning. Voltage and current sensors connected to an ESP32 controller continuously monitor electrical parameters, transmitting waveform data to cloud platforms via MQTT and Wi-Fi. The IEEE Power Quality Disturbance (PQD) dataset (≈11,000 samples across six classes) is used to train and test a Convolutional Neural Network (CNN) after noise filtering, normalization, and waveform segmentation. Experimental results show the CNN model achieves 98.1% classification accuracy (precision 97.8%, recall 98.0%, F1 97.9%), outperforming Random Forest (95.2%) and SVM (93.6%). Apache Spark and cloud storage (Firebase/AWS/ThingSpeak) support scalable, low-latency processing, with an average system response time under two seconds. A web dashboard provides real-time waveform visualization, disturbance alerts, and historical analysis. The proposed system improves monitoring efficiency, fault detection capability, and reliability, making it suitable for smart grid and intelligent power system applications.

Keywords: Power Quality Monitoring, Internet of Things (IoT), Big Data Analytics, Real-Time Analysis, Smart Grid.

I. INTRODUCTION

The rapid expansion of modern electrical systems has significantly increased the use of sensitive electronic equipment across industrial, commercial, and information-technology environments, all requiring stable, uninterrupted power [1]. Power quality — the consistency and reliability of voltage, current, and frequency within acceptable limits — is affected by disturbances such as voltage sag and swell (temporary voltage decreases/increases), harmonics from nonlinear loads that distort the waveform, and frequency variations [2]. Traditional monitoring systems provide only limited coverage and periodic rather than continuous, real-time measurement, which is increasingly insufficient as power systems grow more complex [3].

These limitations have direct consequences: sensitive devices may malfunction or fail under poor power quality, and in industrial settings this causes production losses and higher maintenance costs. Conventional systems typically lack real-time data acquisition and advanced data analysis, so fault detection is often delayed, prolonging disturbances and increasing energy losses [4], [5]. The Internet of Things (IoT) addresses the acquisition gap through smart sensors that continuously monitor voltage, current, and frequency and transmit data to centralized platforms, enabling remote monitoring and rapid response [6]. Big data analytics complements this by processing the resulting high-volume data streams to identify patterns, detect anomalies, and predict faults proactively [7]. Combining IoT and big data analytics therefore yields a monitoring system capable of real-time analysis and intelligent, adaptive decision-making.

This paper develops and evaluates an IoT-based real-time power quality monitoring system that integrates ESP32-based sensing, MQTT/Wi-Fi communication, cloud storage, Apache Spark-based big data processing, and a Convolutional Neural Network (CNN) for

automatic disturbance classification, benchmarked against Random Forest and SVM on the IEEE Power Quality Disturbance dataset, with results delivered through a real-time visualization dashboard.

A key design consideration is that no individual technology in this stack is new in isolation — IoT sensing, cloud storage, big data processing, and CNN classification have each been studied extensively for power-quality applications — but they are rarely evaluated together as a single, working pipeline from sensor to decision. This paper's contribution is therefore less about any one component and more about demonstrating that the four layers can be integrated without the accuracy, latency, or scalability of any individual layer being compromised by the presence of the others, which is validated quantitatively in Section IV through classification accuracy, end-to-end response time, and processing-scalability results measured on the same deployed system.

II. LITERATURE REVIEW

Syed et al. [1] survey smart-grid big-data-analytics technologies and techniques, establishing the broader data-management context this work operates within. Tabassum et al. [2] demonstrate real-time power-quality enhancement in smart grids using IoT and adaptive neuro-fuzzy systems, an intelligent-control approach complementary to the classification-focused method used here. Bagdadee et al. [3] develop an IoT-based wireless sensor network specifically for power-quality control in smart grids, validating the sensor-network architecture adopted in Section III. Mallala et al. [4] present a practically implemented IoT-enabled smart power-quality analysis system for three-phase electrical systems, confirming feasibility of hardware-level IoT power-quality monitoring similar to the ESP32-based setup used in this study.

Rabie et al. [5] review the state of the art in cloud-, IoT-, and big-data-based smart electrical grids, and Majhi and Mohanty [6] provide a comprehensive review of IoT applications across power systems, both supporting the architectural choices in Section III. Rajendran et al. [7] develop intelligent power-quality management for renewable-energy-integrated smart grids using deep learning, directly paralleling the CNN-based classification approach used here. Rao and Sushama [8] propose an IoT-based sensor technology for improving reliability and power quality in smart-grid systems, reinforcing the case for sensor-driven monitoring over periodic manual inspection.

Among the existing-research works most directly relevant to this study: Tabassum et al. [9] provide a comprehensive exploration of IoT-enabled smart-grid power-quality issues, solutions, and challenges, discussing mitigation approaches such as fuzzy logic and neural networks alongside scalability and interoperability concerns. Beniwal et al. [10] critically analyze methodologies for detection and classification of power-quality events in smart grids, reviewing signal-processing and AI-based techniques and the role of IoT and 5G in enabling fast data transmission. Luo et al. [11] examine power-quality challenges arising from nonlinear loads and distributed-energy-resource integration, reviewing analysis methods, compensation devices, and control strategies for microgrids and distribution networks.

On the deep-learning-for-classification side specifically, Li et al. [12] introduce a high-resolution dataset of EV-charging responses under varied power-quality disturbances, illustrating the growing availability of benchmark data for this task; Sekar et al. [13] propose an improved deep-learning-based power-quality disturbance detection approach; Wang et al. [14] classify power-quality disturbances using compressed sensing combined with deep convolutional neural networks; and Han et al. [15] develop an efficient CNN-based atomic-decomposition algorithm for power-quality disturbance signals. Across these works, CNN and other deep architectures consistently outperform classical signal-processing and shallow-ML approaches for waveform classification, but few studies combine this classification accuracy with a complete, working IoT-to-cloud-to-dashboard pipeline evaluated end-to-end — the integration gap this paper addresses.

III. METHODOLOGY

International Journal Of Innovative Trends In Multi Disciplinary Scientific Research
ISSN (Online): 3139 – 2687
(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

A. System Architecture

The proposed system uses a six-layer architecture: Data Acquisition, IoT Communication, Cloud Storage, Data Processing, Machine Learning, and Visualization/Alert layers (Fig. 1). Voltage and current sensors continuously monitor the power system and feed measurements to an ESP32 controller, which acquires sensor data and manages wireless communication. Waveform data is transmitted via Wi-Fi/MQTT to cloud platforms, then preprocessed and feature-extracted before being supplied to the CNN classifier, which identifies disturbances such as sag, swell, harmonics, and interruptions. Classified results and alerts are finally displayed on a real-time monitoring dashboard.

Layering the system this way keeps each stage independently replaceable: the sensing hardware in Section III-B, the communication protocol in Section III-C, and the classifier in Section III-E can each be upgraded (for example, swapping MQTT for a different IoT protocol, or CNN for a hybrid CNN-LSTM model) without redesigning the other layers, provided the interfaces between them remain consistent. This modularity is also what makes the direct three-way comparison between SVM, Random Forest, and CNN in Section IV possible: all three classifiers consume the same preprocessed, feature-extracted data from the identical upstream pipeline, isolating classifier choice as the only varying factor in the comparison.

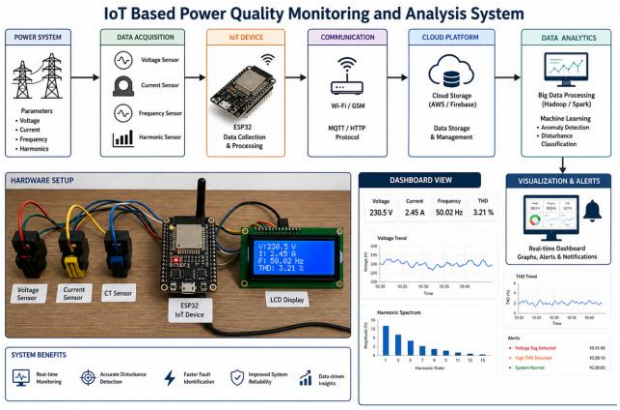


Fig. 1. IoT-based power quality monitoring and analysis system architecture.

B. Dataset and Data Acquisition

The IEEE Power Quality Disturbance (PQD) dataset provides standard waveform disturbances (normal, sag, swell, harmonics, flicker, interruption, oscillatory transients) generated per IEEE power-quality standards, comprising approximately 11,000 high-frequency-sampled time-series voltage waveforms used for CNN training and evaluation. Hardware acquisition used a ZMPT101B voltage sensor and ACS712 current sensor connected to an ESP32 controller with built-in Wi-Fi (Table 1), continuously digitizing voltage/current waveforms for transmission.

Component	Specification
ESP32	IoT Controller
Voltage Sensor	ZMPT101B
Current Sensor	ACS712
Wi-Fi Module	Built-in ESP32
Laptop	Intel i5, 8 GB RAM

TABLE 1. HARDWARE COMPONENTS USED FOR EXPERIMENTAL SETUP

C. IoT Communication and Big Data Framework

MQTT, a lightweight publish-subscribe protocol suited to low-power IoT devices, was used alongside HTTP for cloud communication, minimizing bandwidth and transmission overhead. Waveform data was stored across Firebase (real-time database/fast sync), AWS IoT (scalable infrastructure), and ThingSpeak (visualization), while Apache Spark and Hadoop provided distributed, parallel processing of the resulting large-scale time-series data, reducing processing latency and enabling simultaneous analysis of multiple waveform streams.

The choice of MQTT over heavier protocols such as HTTP-only polling is significant for continuous waveform monitoring specifically: because MQTT uses a publish-subscribe model rather than repeated request-response polling, the ESP32 controller can push new waveform data to the cloud as soon as it is captured, rather than waiting for the cloud platform to request it, which is what keeps end-to-end latency low enough (Section IV-E) to support near-real-time disturbance alerting rather than only periodic, delayed reporting typical of legacy SCADA-style monitoring.

D. Data Preprocessing and Feature Extraction

Raw waveforms were denoised using moving-average filtering and wavelet denoising, then scaled via Min–Max normalization:

$$xnorm = (x - xmin) / (xmax - xmin) \quad ...(1)$$

and segmented into fixed-length windows (128/256/512 samples), each representing one disturbance event. Time-domain features (RMS, mean, standard deviation, peak) were computed, with RMS voltage:

$$VRMS = \sqrt{[(1/N) \Sigma vi^2]} \quad ...(2)$$

found especially discriminative — decreasing during sag, increasing during swell, and dropping sharply during interruptions. Frequency-domain features were obtained via FFT:

$$X(k) = \Sigma x(n)\, e^{-j2\pi kn/N}, \quad n=0..N-1 \quad ...(3)$$

and Total Harmonic Distortion:

$$THD = \sqrt{(\Sigma Vn^2, n\geq 2)} / V1 \quad ...(4)$$

which rose sharply under harmonic disturbance conditions, confirming its value for harmonic detection. Together, the time-domain statistics and frequency-domain spectral features gave the SVM and Random Forest baselines a fixed, interpretable representation of each waveform segment, whereas the CNN classifier (Section III-E) was instead trained to learn its own internal feature representation directly from the segmented raw waveform — allowing a direct comparison between hand-engineered and automatically learned features under otherwise identical preprocessing and evaluation conditions.

E. Classification Models

The dataset was split 70% training / 15% validation / 15% testing. Random Forest and SVM were implemented as baseline classifiers using the extracted time- and frequency-domain features. The CNN model — the primary classifier — used an input layer, convolution layers with ReLU activation, pooling layers, a fully connected layer, and a softmax classifier, learning waveform features automatically from segmented signals without manual feature engineering, and was trained for 20 epochs using the Adam optimizer with categorical cross-entropy loss.

F. Performance Evaluation Metrics

Software Tool	Purpose
Python	Model development
Google Colab	Model training
TensorFlow / Keras	CNN implementation
Scikit-learn	Performance evaluation
MATLAB	Signal visualization

TABLE 2. SOFTWARE TOOLS USED

$$Accuracy = (TP+TN) / (TP+TN+FP+FN) \quad ...(5)$$

$$Precision = TP / (TP+FP) \quad ...(6)$$

$$Recall = TP / (TP+FN) \quad ...(7)$$

$$F1 = 2 \times (Precision \times Recall)/(Precision+Recall) \quad ...(8)$$

IV. RESULTS AND DISCUSSION

A. Dataset Distribution

Table 3 summarizes the ≈11,000-sample dataset across six disturbance classes (2000 samples each for normal, sag, swell, harmonics; 1500 each for flicker and interruption), split 70/15/15 into training (7700), validation (1650), and testing (1650) subsets for CNN development.

Disturbance Type	Samples
Normal	2000
Voltage Sag	2000
Voltage Swell	2000
Harmonics	2000
Flicker	1500
Interruption	1500

TABLE 3. DISTRIBUTION OF POWER QUALITY DISTURBANCE CLASSES

B. CNN Training Behavior

Fig. 2 shows training and validation accuracy rising rapidly over the first several epochs and converging near 98%, with validation accuracy closely tracking training accuracy throughout, indicating minimal overfitting. Correspondingly, training and validation loss decreased steadily and stably across all 20 epochs

International Journal Of Innovative Trends In Multi Disciplinary Scientific Research
ISSN (Online): 3139 – 2687
(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

without oscillation, confirming effective optimization of the CNN parameters.

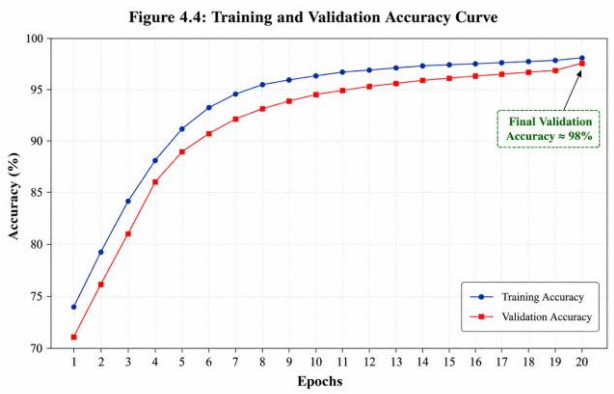


Fig. 2. Training and validation accuracy curve of the CNN model.

C. CNN Classification Performance

On the held-out test set, the CNN model achieved 98.1% accuracy, 97.8% precision, 98.0% recall, and 97.9% F1-score (Table 4), reflecting both reliable disturbance detection and few false positives. The confusion matrix (Fig. 3) confirms most classes were identified correctly, with minor confusion only between waveforms sharing similar magnitude/frequency signatures — sag occasionally misclassified as interruption (both involve reduced voltage magnitude), and flicker occasionally confused with harmonics (both involve frequency-domain variation).

Metric	Value
Accuracy	98.1%
Precision	97.8%
Recall	98.0%
F1-Score	97.9%

TABLE 4. PERFORMANCE METRICS OF THE PROPOSED CNN MODEL

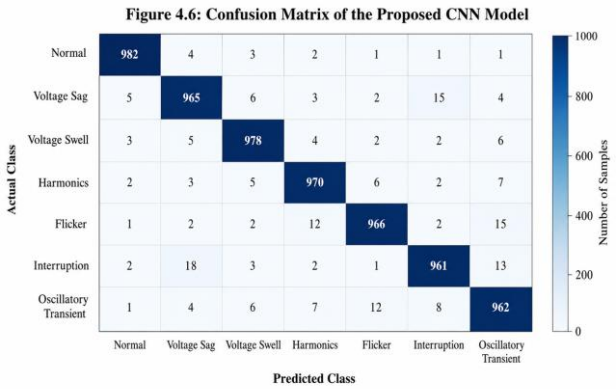


Fig. 3. Confusion matrix of the CNN model for disturbance classification.

D. Comparative Analysis of Classification Models

Table 5 compares SVM, Random Forest, and CNN under identical dataset and testing conditions. SVM achieved 93.6% accuracy with moderate complexity and training time, limited by its reliance on hand-crafted features for complex, nonlinear disturbance patterns. Random Forest improved to 95.2% accuracy with lower complexity and faster training via ensemble decision trees, but remained dependent on manually extracted features. CNN achieved the best accuracy (98.1%) by learning discriminative waveform features directly from raw signal data, at the cost of higher computational complexity and longer training time — a trade-off justified by the accuracy gain for a monitoring application where classification correctness is paramount.

It is worth noting that the accuracy gap between Random Forest and CNN (2.9 percentage points) is smaller than the gap between SVM and Random Forest (1.6 points) is large relative to the added complexity, suggesting diminishing but still meaningful returns from deeper architectures on this dataset. For deployments where training-time or on-device inference cost is tightly constrained, Random Forest's 95.2% accuracy at low complexity may represent an acceptable compromise; for centralized, cloud-based classification as implemented here, however, CNN's higher accuracy is achievable without a corresponding latency penalty at inference time, since only training — not real-time classification — carries the larger computational cost.

Model	Accuracy	Complexity	Training Time
SVM	93.6%	Medium	Medium
Random Forest	95.2%	Low	Low
CNN	98.1%	High	High

TABLE 5. COMPARATIVE PERFORMANCE ANALYSIS OF CLASSIFICATION MODELS

E. Real-Time Monitoring and Dashboard

The IoT pipeline achieved stable, continuous waveform transmission with an average end-to-end response time under two seconds and minimal packet loss, generating real-time alerts whenever sag, swell, or harmonic conditions were detected. Fig. 4 shows the web dashboard, which displays live voltage waveforms, harmonic spectra, disturbance notifications, and historical trend data, improving operator awareness and simplifying fault diagnosis. Apache Spark-based processing maintained stable performance as data volume grew, supporting scalability to larger, multi-node smart-grid deployments.



Fig. 4. Dashboard visualization of the proposed IoT-based monitoring system.

F. Discussion

The consistent ranking CNN > Random Forest > SVM (Table 5) mirrors the pattern seen in prior deep-learning-for-PQD studies [13], [14], [15], and reflects CNN's ability to learn hierarchical waveform representations rather than depend on hand-crafted RMS/FFT/THD features alone, though those features remain useful for interpretability and for training the baseline models. Equally important to raw classification accuracy is that the gains held up in a real, working IoT pipeline rather than an offline classification benchmark alone: sub-two-second response time and stable Spark-based processing under continuous data ingestion demonstrate that the 98.1% accuracy reported in Table 4 is achievable in a deployed, real-time monitoring context, not only in controlled offline testing. This end-to-end validation — sensor to cloud to classifier to dashboard — is what distinguishes the proposed framework from classification-only prior work and supports its applicability to smart-grid, industrial, and renewable-energy-integrated power systems.

V. CONCLUSION

This paper presented an IoT-based real-time power-quality monitoring and analysis system integrating ESP32-based sensing, MQTT/cloud communication, Apache Spark-based big data processing, and a CNN classifier trained on the IEEE PQD dataset. The CNN model achieved 98.1% classification accuracy, precision of 97.8%, recall of 98.0%, and F1-score of 97.9%, outperforming Random Forest (95.2%) and SVM (93.6%) by automatically learning discriminative waveform features rather than relying on manual feature engineering.

The complete pipeline delivered stable cloud communication, sub-two-second average response time, and a real-time dashboard providing live waveform visualization, disturbance alerts, and historical analysis. These results confirm that combining IoT-based acquisition, big data analytics, and deep-learning classification yields a scalable, reliable, and accurate solution for power-quality monitoring, suitable for smart grid, industrial, and renewable-energy-integrated electrical systems.

More broadly, the fact that CNN's accuracy advantage over Random Forest and SVM (Table 5) was preserved end-to-end — through IoT transmission, cloud storage, and Spark-based processing — rather than only in offline benchmark testing, is the result most relevant to practitioners considering deployment. It indicates that the primary cost of adopting a CNN-based classifier in this setting is the higher training and computational complexity noted in Table 5, not any loss of real-world classification accuracy relative to what is achievable offline, which supports CNN as the preferred classifier for production power-quality monitoring deployments of this kind rather than only for research benchmarking.

Future Scope

Future work may explore LSTM, GRU, and hybrid CNN-LSTM architectures for improved disturbance prediction and time-series analysis, edge computing to reduce cloud dependency and further improve response speed, expansion to large-scale multi-node smart-grid deployments, integration with renewable energy and EV charging infrastructure, predictive-maintenance and AI-based fault diagnosis, and cybersecurity mechanisms for secure IoT communication and cloud data protection. Extending the confusion-matrix analysis in Section IV-C into a targeted retraining strategy — specifically addressing the sag/interruption and flicker/harmonics confusion pairs identified there — represents a lower-effort near-term improvement that could push overall accuracy beyond 98.1% without requiring a change in model architecture.

ACKNOWLEDGMENT

I am greatly indebted forever to my guide Alfiya Mahat and HOD K .Chandra Obula Reddy and to all teaching and non teaching staff who supported me directly and indirectly to complete my work. I am sincerely thankful to my Principal Dr. S.K. Biradar for their continued encouragement and active interest in my progress throughout the work I am grateful to be an M.Tech Electrical Power System student at Matsyodari Shikshan Sansthas College of Engineering and Technology, Jalna, Maharashtra.

REFERENCES

[1] D. Syed, A. Zainab, A. Ghrayeb, S. S. Refaat, H. Abu-Rub, and O. Bouhali, "Smart Grid Big Data Analytics: Survey of Technologies, Techniques, and Applications," IEEE Access, vol. 9, pp. 59564–59585, 2021.

[2] S. Tabassum, A. R. Vijay Babu, and D. K. Dheer, "Real-time power quality enhancement in smart grids through IoT and adaptive neuro-fuzzy systems," Sci. Technol. Energy Transit., vol. 79, 2024.

[3] A. H. Bagdadee, M. Z. Hoque, and L. Zhang, "IoT Based Wireless Sensor Network for Power Quality Control in Smart Grid," Procedia Comput. Sci., vol. 167, pp. 1148–1160, 2020.

[4] B. Mallala, R. R. Manyam, J. Saini, M. F. N. Tajuddin, and S. B. Thanikanti, "IoT enabled smart power quality analysis in three phase electrical systems with practical implementation," Sci. Rep., vol. 15, no. 1, p. 39665, 2025.

[5] A. H. Rabie, A. I. Saleh, and H. A. Ali, "Smart electrical grids based on cloud, IoT, and big data technologies: state of the art," J. Ambient Intell. Humaniz. Comput., vol. 12, no. 10, pp. 9449–9480, 2021.

[6] A. A. K. Majhi and S. Mohanty, "A Comprehensive Review on Internet of Things Applications in Power Systems," IEEE Internet Things J., vol. 11, no. 21, pp. 34896–34923, 2024.

[7] P. Rajendran, J. Ranga, P. V. Prasad, B. Mallala, G. Senthilkumar, and L. N., "Development of Intelligent Power Quality Management in Renewable Energy System in Smart Grid using Deep Learning," in Proc. 2024 Int. Conf. Inventive Computation Technologies (ICICT), 2024, pp. 1178–1182.

[8] S. P. C. Rao and M. Sushama, "An IoT-Based Sensor Technology for Improving Reliability and Power Quality in Smart Grid Systems," Int. J. Electr. Electron. Eng. Telecommun., vol. 12, no. 4, pp. 264–271, 2023.

[9] S. Tabassum, A. R. Vijay Babu, D. K. Dheer, F. F. Rui-Ming, and Q. Q. Liao, "A comprehensive exploration of IoT-enabled smart grid systems: power quality issues, solutions, and challenges," Sci. Technol. Energy Transit., vol. 79, 2024.

[10] R. K. Beniwal, M. K. Saini, A. Nayyar, B. Qureshi, and A. Aggarwal, "A Critical Analysis of Methodologies for Detection and Classification of Power Quality Events in Smart Grid," IEEE Access, vol. 9, pp. 83507–83534, 2021.

[11] A. Luo, Q. Xu, F. Ma, and Y. Chen, "Overview of power quality analysis and control technology for the smart grid," J. Mod. Power Syst. Clean Energy, vol. 4, no. 1, pp. 1–9, 2016.

[12] H. Li, Y. Zhang, S. Yang, and X. Liu, "High-resolution Dataset of Electric Vehicle Charging Responses Under Varied Power Quality Disturbances," Sci. Data, vol. 13, no. 1, p. 403, 2026.

[13] K. Sekar, K. Kanagarathinam, S. Subramanian, E. Venugopal, and C. Udayakumar, "An Improved Power Quality Disturbance Detection Using Deep Learning Approach," Math. Probl. Eng., vol. 2022, p. 7020979, 2022.

[14] J. Wang, Z. Xu, and Y. Che, "Power Quality Disturbance Classification Based on Compressed Sensing and Deep Convolution Neural Networks," IEEE Access, vol. 7, pp. 78336–78346, 2019.

[15] Y. Han, Y. Feng, P. Yang, L. Xu, and A. S. Zalhaf, "An efficient algorithm for atomic decomposition of power quality disturbance signals using convolutional neural network," Electr. Power Syst. Res., vol. 206, p. 107790, 2022.

Authors Biography

Author1



Ms. Shaikh Nagma Anis is pursuing M. TECH degree in stream of Electrical Power System from Mss's college of Engineering and technology, Jalna, DR BATU University, Lonere. She completed her B.E in the stream of Electrical Engineering from Mss's college of Engineering and technology, Jalna, DR BAMU University.

Email Id: sk5017283@gmail.com

Author2



Prof.Miss Alfiya A. Mahat received M.Tech in Electronics engineering from Savitribai Phule women's College of engineering. She is currently working as Assistant Professor in Department of Electrical Engineering & Technology at MSS's College of Engineering and Technology,Jalna.

Email Id: alfiya704@gmail.com