

MACHINE LEARNING BASED INTELLIGENT POWER QUALITY MONITORING AND DISTURBANCE CLASSIFICATION

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ABSTRACT

The quality of electrical power supplied to homes, industries, and commercial buildings has become a serious concern as the use of sensitive electronic equipment has grown. Voltage sags, swells, interruptions, harmonics, transients, flicker, and notches can cause equipment malfunction, data loss, overheating, and production stoppages. At the same time, the increasing use of power electronic converters, variable speed drives, and renewable energy sources has made such disturbances more frequent. This paper presents a machine learning based intelligent power quality monitoring and disturbance classification system that captures voltage waveforms, extracts signal features, and automatically identifies the type of disturbance present.

The monitoring hardware consists of a step-down voltage transformer and a current sensor, followed by a signal conditioning circuit that scales and offsets the signal for a microcontroller analog-to-digital converter sampling at several kilohertz. Waveform windows of ten cycles are transmitted to a processing unit. To build a large and balanced training set, disturbance signals are also generated synthetically using parametric equations consistent with the IEEE 1159 recommended practice, covering normal supply, sag, swell, interruption, harmonics, oscillatory transient, impulsive transient, flicker, notch, and combined disturbances such as sag with harmonics, with white noise added at several signal-to-noise ratios.

Signal processing forms the core of the feature extraction stage. The discrete wavelet transform decomposes each waveform into detail and approximation levels, and the energy, standard deviation, and entropy of the coefficients at each level are computed. The fast Fourier transform provides harmonic magnitudes and total harmonic distortion, and time domain features such as RMS variation, peak value, crest factor, and kurtosis are added. These features are used to train and compare k-nearest neighbours, a support vector machine, a decision tree, random forest, gradient boosting, and a multilayer perceptron.

The models are evaluated using accuracy, precision, recall, F1 score, and confusion matrices across noise levels. Random forest and the support vector machine achieved the highest accuracy and retained good performance even at low signal-to-noise ratios, while wavelet energy features proved the most informative. A dashboard displays the live waveform, RMS voltage, frequency, total harmonic distortion, the classified disturbance type, and a log of events with time stamps and durations.

The proposed system offers a low-cost alternative to commercial power quality analysers for use in academic laboratories, small industries, and distribution substations. It helps engineers identify the source and nature of disturbances and plan corrective measures such as filters and voltage regulators. Future work includes three-phase monitoring, deployment of the classifier on the microcontroller itself, and the use of deep learning directly on raw waveforms.

I. INTRODUCTION

Electrical power is expected to be delivered as a pure sinusoidal voltage at a constant magnitude and frequency. In practice, the voltage at the point of use is affected by faults on the network, switching of large loads and capacitor banks, lightning strikes, and the operation of nonlinear loads. The term power quality describes how closely the actual supply matches the ideal waveform, and any deviation that causes equipment to fail or misoperate is treated as a power quality problem.

The importance of power quality has increased considerably in recent years. Computers, programmable controllers, medical equipment, and communication systems are sensitive to even brief voltage sags or transients. Meanwhile, the widespread use of switched-mode power supplies, LED lighting, inverters, and variable frequency drives injects harmonic currents into the network, and the connection of solar and wind generation introduces fluctuations. Industries report significant financial losses from process interruptions and equipment damage caused by poor power quality, and utilities face growing pressure to monitor and report supply quality.

Monitoring power quality requires both measurement and interpretation. Commercial power quality analysers record voltage and current waveforms and compute parameters such as RMS, frequency, and harmonic distortion, but they are expensive and often require an expert to examine recorded events and decide what type of disturbance occurred. Since a monitoring device can capture thousands of events, manual classification is slow and impractical. Automatic classification based on signal processing and machine learning offers a way to label events quickly and consistently, which is essential for diagnosing their causes.

This paper describes an intelligent power quality monitoring system that combines a low-cost acquisition circuit, signal processing based feature extraction, and machine learning classification. Voltage waveforms are sampled, features are computed using the wavelet transform, the Fourier transform, and time domain statistics, and a trained classifier identifies the disturbance class. The system is trained on both synthetic and measured signals and is evaluated under different noise levels. A dashboard presents live measurements and a history of classified events to support maintenance and corrective action.

II. LITERATURE SURVEY

Power quality has been studied as a distinct engineering discipline since the growth of sensitive electronic loads made supply disturbances a practical concern. Early

research concentrated on defining and characterising the different disturbance types, and international recommended practices were established to classify events such as sags, swells, interruptions, transients, harmonics, and flicker according to their magnitude and duration. These definitions formed the basis for measurement instruments that computed RMS values over each half cycle and flagged events when the voltage moved outside set thresholds. Studies of field measurements across distribution networks showed that voltage sags caused by faults on neighbouring feeders are the most common and most costly disturbance for industrial customers, while harmonics are the most persistent. Researchers observed, however, that threshold-based detection alone cannot distinguish between disturbances with similar RMS behaviour, such as a sag and a sag accompanied by harmonics, and that more detailed analysis of the waveform is needed for reliable classification.

Signal processing techniques for extracting power quality features have been studied extensively. The fast Fourier transform is well suited to analysing stationary signals and computing harmonic content and total harmonic distortion, but it provides no information about when a disturbance begins or ends. The short-time Fourier transform adds time localisation using a sliding window, but its fixed window length limits resolution for both fast transients and slow variations. The discrete wavelet transform addresses this through multi-resolution analysis, decomposing a signal into frequency bands with time resolution appropriate to each band. Many studies have shown that the energy and entropy of wavelet detail coefficients change characteristically for each disturbance type, making them effective features. The S-transform and the Hilbert-Huang transform have also been proposed, with authors reporting strong time-frequency localisation, although at a higher computational cost than the wavelet transform.

Machine learning classifiers have been applied to power quality features with considerable success. Early studies used artificial neural networks and fuzzy logic systems trained on wavelet features, reporting accuracies above ninety percent for single disturbances. Support vector machines were later found to perform very well because they handle high-dimensional feature spaces and generalise effectively from moderate amounts of training data. Decision trees and rule-based classifiers were proposed for their speed and transparency, which suits embedded implementation. More recently, ensemble methods such as random forest and gradient boosting have achieved some of the best reported results, particularly for combined disturbances and in the presence of noise. Comparative studies have highlighted that accuracy often drops sharply when noise is added to the signals, and that the robustness of the chosen feature set to noise is as important as the choice of classifier. Many authors therefore report results at several signal-to-noise ratios.

The generation of training data has received particular attention because real disturbance recordings are scarce and unevenly distributed across classes. Most studies generate synthetic signals using parametric mathematical models in which the amplitude, duration, start time, frequency content, and phase of each disturbance are varied randomly within ranges consistent with recommended practice. This allows thousands of labelled signals to be produced for every class, including combined disturbances such as sag with harmonics or swell with transients. Researchers have

added Gaussian white noise at various levels to simulate measurement noise. Some studies have validated models trained on synthetic data using recordings from laboratory test benches or real distribution networks, generally finding that performance is maintained when the synthetic parameter ranges are chosen realistically, but that attention must be paid to sampling rate, anti-aliasing, and measurement noise in the actual acquisition hardware.

Recent research has moved towards intelligent monitoring systems that integrate acquisition, analysis, and reporting. Low-cost monitoring devices based on microcontrollers and embedded processors with voltage and current sensors have been developed, some transmitting data wirelessly to cloud servers where classification is performed. Other studies have implemented classifiers directly on embedded hardware to allow real-time decisions at the point of measurement. Deep learning methods, particularly one-dimensional convolutional networks and recurrent networks applied to raw waveforms, have been reported to learn features automatically and achieve high accuracy, but they require large datasets and more computing resources. Several authors note that feature-based methods using wavelet and Fourier analysis remain attractive for low-cost systems because of their efficiency and interpretability. The system proposed in this paper follows this approach, combining practical acquisition hardware, well-established signal processing features, and machine learning classifiers evaluated under realistic noise conditions.

III. SYSTEM ANALYSIS

The power quality monitoring system measures the supply voltage at a point of interest and determines whether a disturbance is present and what type it is. A step-down voltage transformer and a Hall-effect current sensor produce low-level signals, and a conditioning circuit with a voltage divider, DC offset, and anti-aliasing low-pass filter prepares them for the microcontroller analog-to-digital converter, which samples at a rate high enough to capture harmonics and transients. The samples are grouped into ten-cycle windows and sent to a processing unit over a serial or Wi-Fi link. Each window is normalised, and features are extracted using a multi-level discrete wavelet transform, the fast Fourier transform, and time domain statistics. The trained classifier assigns the window to one of the normal, single, or combined disturbance classes. RMS voltage, frequency, and total harmonic distortion are computed continuously, and detected events are logged with time, duration, class, and severity. A dashboard displays live measurements, waveforms, and the event history for engineers.

Existing System

In many industries, commercial buildings, and distribution substations, power quality is either not monitored at all or is monitored only after a problem has occurred. When equipment fails repeatedly, an engineer brings a portable power quality analyser, records data for some days, and then studies the recorded events manually. Such analysers are expensive, and only a small number are usually available, so continuous monitoring at many locations is not practical. Basic energy meters and protection relays measure RMS voltage and current but provide little information about disturbance type. Where event detection is performed, it typically uses fixed RMS

thresholds that detect sags, swells, and interruptions but cannot identify harmonics, transients, notches, or combined disturbances reliably. Classifying the large number of recorded events requires expert knowledge and considerable time, and different engineers may interpret the same waveform differently. As a result, the causes of disturbances often remain unidentified, corrective measures are delayed, and equipment continues to be exposed to poor supply conditions.

Disadvantages of Existing System

- Power quality is often monitored only after equipment has already failed.
- Commercial power quality analysers are expensive and available in small numbers.
- Energy meters and relays give little information about the type of disturbance.
- Fixed RMS thresholds cannot identify harmonics, transients, or notches reliably.
- Combined disturbances are difficult to recognise with threshold methods.
- Manual classification of recorded events is slow and requires expert knowledge.
- Different engineers may classify the same waveform differently.
- Measurement noise reduces the reliability of simple detection methods.
- Event records are not organised for trend analysis over time.
- Causes of disturbances remain unidentified, delaying corrective action.

Proposed System

The proposed system is a low-cost intelligent power quality monitor that uses signal processing and machine learning to classify disturbances automatically. A voltage transformer, a current sensor, and a signal conditioning circuit feed a microcontroller that samples the waveform and sends ten-cycle windows to a processing unit. A training dataset of normal supply, sag, swell, interruption, harmonics, oscillatory transient, impulsive transient, flicker, notch, and combined disturbances is generated synthetically from parametric models with random parameters and added noise at several signal-to-noise ratios, and is supplemented with measured laboratory signals. Features are extracted using an eight-level discrete wavelet transform, giving energy, standard deviation, and entropy for each level, together with FFT harmonic magnitudes, total harmonic distortion, RMS variation, crest factor, skewness, and kurtosis. K-nearest neighbours, a support vector machine, a decision tree, random forest, gradient boosting, and a multilayer perceptron are trained and compared using accuracy, precision, recall, F1 score, and confusion matrices at each noise level. The best model classifies live windows, and a dashboard shows waveforms, parameters, and an event log.

Advantages of Proposed System

- Classifies ten types of single and combined power quality disturbances automatically.
- Uses low-cost sensors and a microcontroller instead of an expensive analyser.

- Wavelet features capture both the timing and frequency content of disturbances.
- FFT features measure harmonic content and total harmonic distortion accurately.
- Trained on synthetic and measured signals for a large, balanced dataset.
- Evaluated at several noise levels to confirm robustness in real conditions.
- Compares six classifiers and selects the most accurate and robust one.
- Logs every event with time, duration, type, and severity for later analysis.
- Displays live RMS voltage, frequency, THD, and waveforms on a dashboard.
- Helps engineers identify disturbance causes and plan corrective measures.

IV. METHODOLOGY

The methodology begins with the design of the acquisition hardware, in which the mains voltage is stepped down, scaled with a resistive divider, offset to the mid-range of the analog-to-digital converter, and filtered with an anti-aliasing filter before sampling at 6.4 kilohertz. In parallel, a synthetic dataset is generated at the same sampling rate for a fifty hertz fundamental, with each class produced from its parametric equation using randomly chosen magnitude, duration, start time, harmonic order, and transient frequency within standard ranges, and with white noise added at signal-to-noise ratios of twenty, thirty, and forty decibels. Each ten-cycle window is normalised to the nominal peak. The discrete wavelet transform with a Daubechies mother wavelet decomposes the signal into eight levels, and statistical features of each level are computed, together with FFT-based harmonic and distortion features and time domain features. The combined feature set is standardised and reduced by removing highly correlated features. The data is split with stratification, classifiers are tuned using five-fold cross-validation, and the best model is tested with accuracy, precision, recall, F1 score, and confusion matrices on clean and noisy signals and on measured laboratory waveforms.

SYSTEM ARCHITECTURE

Machine learning based intelligent power quality monitoring and disturbance classification

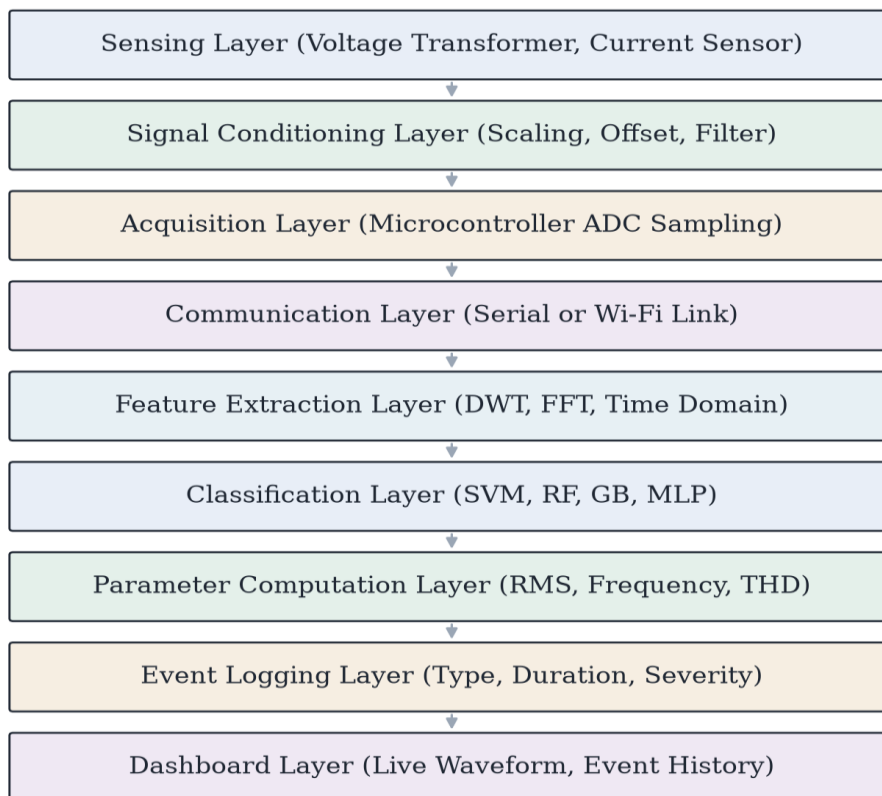


Fig. 1 System Architecture

The architecture of the power quality monitoring system is organised into layers that move from physical measurement to classified events presented to engineers. The Sensing Layer uses a voltage transformer and a Hall-effect current sensor to obtain isolated low-level signals from the supply. The Signal Conditioning Layer scales and offsets these signals and applies anti-aliasing filtering. The Acquisition Layer samples the conditioned signals with the microcontroller ADC and forms ten-cycle windows. The Communication Layer transfers windows to the processing unit over a serial or Wi-Fi link. The Feature Extraction Layer applies the discrete wavelet transform, the fast Fourier transform, and time domain analysis. The Classification Layer holds the trained model that labels each window. The Parameter Computation Layer calculates RMS voltage, frequency, and total harmonic distortion. The Event Logging Layer stores classified events with time, duration, and severity, and the Dashboard Layer displays live waveforms, parameters, classifications, and event history.

V. RESULT AND OUTPUT



VI. CONCLUSION

This paper has presented a machine learning based intelligent power quality monitoring and disturbance classification system. The system combines a low-cost acquisition circuit built from a voltage transformer, a current sensor, signal conditioning, and a microcontroller with signal processing based feature extraction and machine learning classification. It automatically identifies normal supply and nine types of single and combined disturbances, removing the need for slow and inconsistent manual inspection of recorded waveforms.

The work showed that features derived from the discrete wavelet transform are particularly effective, because they capture both the time at which a disturbance occurs and its frequency content. Combining these with FFT-based harmonic features and time domain statistics produced a compact feature set that allowed classifiers to separate even combined disturbances such as sag with harmonics. Generating a large and balanced synthetic dataset from parametric models, and adding measured signals from the laboratory set-up, provided the training data needed for reliable learning.

Among the classifiers compared, random forest and the support vector machine achieved the highest accuracy and maintained strong performance when noise was added at low signal-to-noise ratios, which is important for real field conditions. The dashboard presents live RMS voltage, frequency, total harmonic distortion, waveforms, and a log of classified events, giving engineers the information needed to trace disturbances to their sources and plan corrective measures such as harmonic filters, surge protection, or voltage regulators.

Future work can extend the system to three-phase monitoring with simultaneous current measurement, allowing unbalance and power factor to be assessed as well. Deploying a compact decision tree or quantised model directly on the microcontroller would enable real-time classification at the point of measurement without a separate processing unit. One-dimensional convolutional neural networks applied to raw waveforms, and networks of monitors reporting to a central server, can also be explored for utility-scale monitoring.

REFERENCES

- [1] Kumar, R. D., Prudhviraaj, G., Vijay, K., Kumar, P. S., & Plugmann, P. (2024). Exploring COVID-19 through intensive investigation with supervised machine learning algorithm. In *Handbook of Artificial Intelligence and Wearables* (pp. 145-158). CRC Press.
- [2] Swathi, B., Vijay, K., Sushanth Babu, M., & Dinesh Kumar, R. (2024, November). Machine Learning Techniques in Cloud Based Intrusion Detection. In *The International Conference on Artificial Intelligence and Smart Environment* (pp. 557-564). Cham: Springer Nature Switzerland.
- [3] Sv satyakraishna, shirisha rang, bhargavi nalacheruve. (2024) Prospective investigation on colorectal cancer with SMOTE on machine learning Algorithm
- [4] Dr.G.Vishnu Murthy, BhargaviNalacheruve 1Professor, Department of computer Science & engineering, Anurag University, TS, India. 2Student, Department of computer Science & engineering, Anurag University, TS, India.
- [5] V. N. S. Manaswini, K. K, C. Nigam, S. S. Ali, R. Niranjana, and Suman, "Real-Time Object Detection in Drone Surveillance Using YOLOv5," in *Proc. 2025 3rd Int. Conf. IoT, Communication and Automation Technology (ICICAT)*, Gorakhpur, India, 2025, pp. 1–6, doi: 10.1109/ICICAT68430.2025.11414670.
- [6] B. Soundarya, V. N. S. Manaswini, M. Ayyakrishnan, R. D. Kumar, "Contextual Analysis of Big Data Analytics in Intelligent Transportation Frameworks," in *Intersection of Artificial Intelligence, Data Science, and Cutting-Edge Technologies: From Concepts to Applications in Smart Environment*, Lecture Notes in Networks and Systems, vol. 1353, Cham: Springer, 2025, doi: 10.1007/978-3-031-88304-0_79.
- [7] R. D. Kumar, V. N. S. Manaswini, "Applications of blockchain in smart cities: detecting fake documents from land records using blockchain technology," in *Blockchain for Smart Cities*, Elsevier, 2021, pp. 105–117, doi: 10.1016/B978-0-12-824446-3.00017-X.
- [8] Tejavath Veeramma, Badarla Anil, Guguloth Ravinder, "An advanced movie recommender using collaborative filtering and sentiment analysis," *International Research Journal of Modernization in Engineering Technology and Science*, vol. 7, no. 7, July 2025, doi: 10.56726/IRJMETS81618.
- [9] Ravi Kumar Banoth, Ramana Murthy B V, "Automatic crop recommendation system using LightGBM and decision tree machine learning models," *Journal of Machine and Computing*, vol. 5, no. 1, pp. 343, Jan. 2025, doi: 10.53759/7669/jmc202505026.
- [10] Ravi Kumar Banoth, Dr. B.V. Ramana Murthy, "Smart agriculture through IoT and machine learning for analyzing carbon footprints," in *Proc. Int. Conf. Computer Science and Communication Engineering (ICCSCE)*, Apr. 2025.

[11] Ravi Kumar Banoth, B. V. Ramana Murthy, "Soil image classification using transfer learning approach: MobileNetV2 with CNN," SN Computer Science, vol. 5, art. no. 199, 2024, doi: 10.1007/s42979-023-02500-x.