

An explainable hybrid deep learning approach for power quality disturbance classification

Hasan UZEL 

Akdağmadeni Vocational School, Yozgat Bozok University, Yozgat, 66000, Turkey

Abstract. This study presents a deep learning-based framework for the accurate classification of power quality (PQ) disturbances using time-series and environmental data. Four architectures: artificial neural network (ANN), convolutional neural network (CNN), long short-term memory (LSTM), and a hybrid model were implemented and evaluated on a dataset containing key electrical and environmental features such as voltage sag, harmonics, temperature pollution level. Comprehensive preprocessing, including normalization, correlation assessment of skewness and kurtosis analysis, ensured statistical reliability. Among the evaluated models, the hybrid architecture achieved the best performance, with an accuracy of 98.91% and an F1-score of 98.90%, outperforming all standalone approaches. Model interpretability was enhanced using local interpretable model-agnostic explanations (LIME), which identified feature contributions for individual predictions. A comparison with eight recent studies demonstrated competitive or superior performance in both accuracy and explainability. The integration of high-performing hybrid modeling with interpretable AI makes the proposed system well-suited for real-time PQ monitoring in smart grid environments. Future work may incorporate unsupervised and transfer learning methods to improve adaptability across varying grid conditions and data scarcity scenarios.

Keywords: power quality; deep learning; hybrid; explainable AI; LIME.

1. INTRODUCTION

The increasing complexity of modern electrical grids, driven by renewable energy integration, electric vehicle adoption, and the growing presence of nonlinear loads, has intensified the need for accurate and interpretable detection of power quality (PQ) disturbances [1]. Voltage sags, harmonic distortions [2], frequency fluctuations, and transient events can significantly degrade system efficiency and pose risks to sensitive equipment [3]. As a result, reliable PQ disturbance classification has become essential for smart grid operation and real-time monitoring applications [4].

Traditional machine learning techniques have contributed to PQ analysis; however, they typically depend on manual feature extraction and are limited in capturing the nonlinear and spatiotemporal characteristics of PQ signals [5]. Recent advances in deep learning, including artificial neural networks (ANN), convolutional neural networks (CNN), and long short-term memory (LSTM) networks, have demonstrated strong performance by enabling automatic representation learning from raw or minimally processed data [6]. While ANN models provide general nonlinear modeling but lack spatial and temporal sensitivity [7], CNNs effectively extract spatial features, and LSTMs excel in modeling temporal dependencies in time-series signals [8]. However, standalone models often fall short in learning both spatial and temporal aspects simultaneously.

To address these limitations, this study proposes a hybrid deep learning model that integrates the spatial feature extraction capability of CNNs with the temporal modeling strength of LSTMs. The model is evaluated on a dataset comprising electrical and environmental features, and its performance is compared with standard ANN, CNN, and LSTM architectures. Comprehensive preprocessing and statistical validation techniques are applied to ensure data reliability. Furthermore, explainable artificial intelligence (XAI) methods, specifically local interpretable model-agnostic explanations (LIME), are incorporated to enhance transparency and support decision interpretation in critical grid applications.

The main contributions of this study are as follows:

1. the development of a hybrid architecture that effectively learns spatial and temporal patterns and achieves superior PQ classification accuracy,
2. the integration of LIME-based interpretability to enhance model transparency and support decision reliability, and
3. the implementation of extensive preprocessing and statistical validation procedures to ensure data quality and reproducibility.

2. LITERATURE REVIEW

Power quality disturbance (PQD) classification has been extensively studied due to the increasing integration of renewable energy sources and the sensitivity of modern electrical equipment. Early research primarily relied on manually engineered features and conventional classifiers, while recent advances in deep learning have enabled automatic representation learning from raw or transformed PQ signals.

*e-mail: hasan.uzel@bozok.edu.tr

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Several CNN- and LSTM-based models have been proposed to enhance disturbance identification. Wang *et al.* introduced an ensemble CNN with time-frequency fusion for robust classification [9], whereas Özer *et al.* combined CNN and Bi-LSTM architectures using spectrogram-based representations to classify 29 PQD types [10]. Tian *et al.* highlighted system vulnerabilities by examining adversarial attacks on PQD classifiers and improving robustness through adversarial training [11]. Ekici *et al.* demonstrated the effectiveness of a CNN-based approach using colorized continuous wavelet transform images, achieving high performance on a real-world dataset from the Turkish power grid [12]. Chen *et al.* proposed a regulated 2D deep CNN for microgrid-based PQD classification, addressing frequency deviation through IEC-based synchronization and achieving improved real-time accuracy across 14 disturbance types [13].

Hybrid architectures have also gained traction. Sindi *et al.* proposed a 1D–2D CNN hybrid model mimicking expert signal interpretation [14], while Sekar *et al.* introduced a CNN-LSTM framework that improved detection in renewable energy-integrated systems [15]. Yiğit *et al.* showed that CNN-GRU networks using STFT-derived matrices offer superior accuracy under noisy conditions [16]. Han *et al.* enhanced traditional atomic decomposition by incorporating a CNN-based subdictionary predictor to reduce computational complexity [17]. Iturrino Garcia *et al.* compared FT-MLMVN and STFT-CNN approaches, demonstrating high performance with low computational cost [18].

Broader studies investigated PQ forecasting, system optimization, and energy management. Zjavka developed an incremental AI-based prediction algorithm for off-grid systems [19], while Gonzalez-Abreu *et al.* reviewed PQ impacts on motor efficiency [20]. Aslan *et al.* surveyed deep learning methods for energy prediction in microgrids [21]. Lan *et al.* proposed an SVM- and metaheuristic-based framework for microgrid cost reduction [22]. Malik *et al.* explored digital transformation trends in engineering applications involving PQ and intelligent monitoring [23]. Rajesh *et al.* introduced an optimization-based hybrid control strategy for enhancing PQ in renewable systems [24], and Aljendy *et al.* optimized PV-wind integration and harmonic mitigation using SSA and PSO approaches [25].

Overall, the literature demonstrates a clear transition from traditional methods toward deep learning, hybrid architectures, and explainable AI approaches, underscoring the need for accurate, robust, and interpretable PQ disturbance classification.

3. MATERIAL AND METHOD

This section outlines the dataset, the preprocessing procedures, and the methodological framework used for classifying power quality (PQ) disturbances with deep learning techniques. The study employs a publicly available dataset containing 1000 instances and 12 electrical and environmental features, including voltage sag, harmonics, transient disturbances, reactive power compensation, temperature, pollution level, and wind speed. Prior to model training, preprocessing steps, including normalization and correlation assessment of skewness-kurtosis analysis, were applied to ensure statistical reliability. Four deep

learning architectures (ANN, CNN, LSTM, and Hybrid CNN-LSTM model) were implemented in TensorFlow/Keras under identical training protocols. Model performance was evaluated using standard classification metrics, while interpretability was supported through the LIME framework to ensure robust learning, fair comparison, and strong generalization across diverse PQ scenarios.

3.1. Dataset

Growing grid complexity and increased integration of renewable energy sources have intensified the need for accurate PQ monitoring. The CloudyMTS dataset employed in this study includes essential PQ indicators such as voltage sag, harmonics, transient disturbances, and reactive power compensation [26], complemented by environmental and operational variables such as temperature, pollution level, wind speed, and corrosion index. The dataset features balanced class distribution and standardized numerical values (mean ≈ 0 , SD ≈ 1), making it suitable for both classification and regression tasks. Variables such as voltage stability index and harmonic filtering show strong potential as predictors of PQ issues under varying grid conditions, enabling the development of reliable diagnostic models for predictive maintenance and enhanced grid reliability.

3.2. Data preprocessing

A structured preprocessing pipeline was applied to ensure statistical consistency and prevent information leakage. Data inspection addressed duplicate entries, incorrect types, and physically implausible values, while rare missing values were handled through median imputation. Outliers detected via interquartile range and z-score diagnostics were retained unless physically inconsistent, preserving natural PQ variability.

All continuous variables were standardized using z-score normalization, with normalization parameters computed exclusively from the training split and later applied to validation and test sets to maintain a leakage-free workflow.

As shown in Table 1, all features exhibited skewness and kurtosis values close to zero, indicating symmetric, mesokurtic distributions. This near-normal behavior supports the use of learning algorithms that assume or benefit from normally distributed inputs and minimizes the need for additional transformations. Pairwise Pearson correlations (Fig. 4) further revealed weak linear relationships among features, confirming that each variable contributes independent and complementary information to the classification task. All preprocessing steps involving learned statistics, including imputation and normalization,

Table 1
Skewness and kurtosis values of selected features

Feature	Skewness	Kurtosis
Voltage_Sag	0.117	0.073
Harmonics	-0.049	0.058
Temperature	-0.002	-0.229
Pollution_Level	-0.176	0.155

were fitted solely on the training set and applied unchanged to the validation and test subsets, ensuring a fully leakage-free pipeline. Additional details on data partitioning are provided in Section 3.4.

3.3. Long short-term memory networks

Long short-term memory (LSTM) networks are a specialized form of recurrent neural networks (RNNs) designed to capture temporal dependencies in sequential data through a gated memory-cell structure consisting of input, forget, and output gates [27]. This architecture enables LSTMs to retain relevant historical information and discard outdated or irrelevant signals. In PQ disturbance classification, LSTMs effectively capture the temporal evolution of voltage and current waveforms, especially during nonstationary events such as transients, sags, and harmonic fluctuations.

By processing time-series data sequentially, LSTMs learn complex temporal relationships often missed by feedforward networks. In this study, LSTM was leveraged to enhance classification performance by modeling temporal characteristics of PQ signals, supporting more context-aware and robust decision-making [28].

3.4. Data splitting and validation protocol

To ensure unbiased evaluation, the dataset was divided into training (70%), validation (15%), and test (15%) subsets using stratified sampling to preserve class proportions. Hyperparameter tuning and model selection were performed exclusively on the validation set, while the test set was reserved for final evaluation. A fixed random seed (42) was applied to data splitting, weight initialization, and mini-batch shuffling to ensure reproducibility. Preprocessing steps requiring learned statistics, such as median imputation and normalization, were fitted only on the training

subset and applied unchanged to the validation and test sets, maintaining a leakage-free pipeline consistent with Section 3.2. The performance metrics reported in Section 4 correspond to this final test evaluation.

3.5. Model implementation/Architecture

Four neural architectures: ANN, CNN, LSTM, and a hybrid CNN-LSTM model were implemented using TensorFlow 2.12 (Python 3.10). All models were trained with the Adam optimizer (learning rate = 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$) and optimized using the categorical cross-entropy loss function. Training was performed for 25 epochs with a batch size of 32, and early stopping (patience = 5, monitored on validation loss) was employed to prevent overfitting. A fixed random seed (42) was used for data partitioning, weight initialization, and mini-batch shuffling to ensure complete reproducibility of results.

The ANN consisted of three dense layers (64, 32, 16 units) followed by a Softmax output. The CNN model employed two Conv1D layers (32 and 64 filters), max-pooling, a global average pooling layer, and a dense layer of 32 units before the Softmax output. The LSTM architecture comprised a single LSTM layer with 64 units and a dense layer of 32 neurons. The Hybrid model combined a Conv1D–Pool–Conv1D–GAP branch with an LSTM branch; their outputs were concatenated and passed through dense layers of 64 and 32 units prior to Softmax classification.

ReLU activation was used in ANN and CNN layers, while LSTM layers employed Tanh activation. A 0.20 dropout rate was applied across all models. Input features were standardized using training-set statistics only, ensuring a leakage-free preprocessing pipeline. Because the dataset was balanced, no class weighting was required. Table 2 summarizes the hyperparameters and architectural configurations.

Table 2

Model hyperparameters and architectural details

Model	ANN	CNN (Conv1D)	LSTM	Hybrid (CNN + LSTM)
Input shape	12 features	seq_len \times feat	seq_len \times feat	combined branches
Network architecture (summary)	Dense layers[64, 32, 16], followed by output	Conv1D (32, k = 3) – MaxPool – Conv1D (64, k = 3) – GAP – Dense(32) – Output	LSTM(64)– Dense(32)– Output	CNN branch (Conv1D–Pool–Conv1D–GAP) merged with LSTM(64); Concatenation - Dense[64, 32] – Output
Activation	ReLU (hidden) / Softmax (output)	ReLU (hidden) / Softmax (output)	Tanh (LSTM) / Softmax (output)	ReLU + Tanh / Softmax (output)
Dropout	0.20	0.20	0.20	0.20
Optimizer	Adam	Adam	Adam	Adam
Learning rate	0.001	0.001	0.001	0.001
Loss function	Categorical cross-entropy	Categorical cross-entropy	Categorical cross-entropy	Categorical cross-entropy
Epochs	25	25	25	25
Batch size	32	32	32	32
Notes	He init; z-score normalization; seed = 42	time-frequency or raw windows	return_sequences = False	concatenation fusion; seed = 42

3.6. Convolutional neural network

Convolutional neural networks (CNNs) are widely used to extract spatial patterns from structured data such as images and time-frequency representations [29]. In PQ disturbance classification, CNNs perform effectively when signals are transformed into spectrograms or CWT-based maps [30], enabling the detection of localized features linked to sags, harmonics, transients, and interruptions. Their ability to autonomously learn hierarchical spatial representations reduces the need for manual feature engineering and ensures robust performance under noise. These advantages make CNNs well-suited for real-time PQ monitoring and diagnostic applications [31].

3.7. Artificial neural network

Artificial neural networks (ANNs) are adaptive computational models capable of approximating nonlinear relationships [32] and are widely used in PQ disturbance classification due to their simplicity and fast convergence [33]. However, their performance may lag behind deeper architectures when handling complex temporal or high-dimensional data [34]. In this study, ANN is employed as a baseline model for comparison with more advanced deep learning approaches.

3.8. Local interpretable model-agnostic explanations

The local interpretable model-agnostic explanations (LIME) framework was used to enhance model interpretability by generating local surrogate models, typically linear regressors, through feature perturbation and analysis of the resulting prediction changes. In PQ applications, LIME helps explain why specific disturbances such as sags, harmonics, or transients are identified, offering clear insight into feature contributions. This localized interpretability supports transparent and accountable decision-making for engineers and grid operators in real-time environments [35].

3.9. Proposed model

Figure 1 illustrates the workflow for classifying power quality (PQ) disturbances using the proposed hybrid model, which integrates ANN, CNN LSTM architectures. The hybrid structure employs separate input branches for each network: the ANN branch processes scaled features through dense layers, the CNN branch extracts spatial patterns using convolutional and pooling layers, and the LSTM branch captures temporal dependencies through recurrent layers. These branches are then concatenated and passed through additional dense layers to generate the final classification output.

The methodology begins with data loading and validation, followed by exploratory data analysis (EDA) to examine class distributions, feature histograms, and correlation matrices. Pre-processing steps include target encoding, class balancing via oversampling, dataset partitioning into training, validation test sets, as well as feature scaling and reshaping to ensure compatibility with each model. Four architectures: ANN, CNN, LSTM, and the proposed hybrid model are constructed, trained, and evaluated using accuracy and loss curves, confusion matrices, classification reports, and metrics such as accuracy, precision,

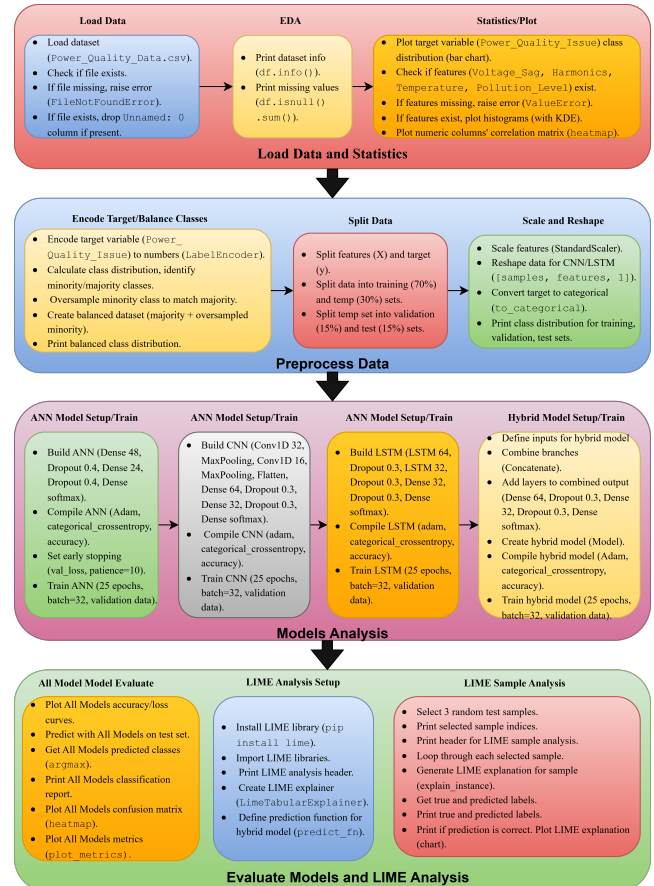


Fig. 1. Flowchart of the power quality classification process with the proposed (hybrid model)

recall, and F1-score. To enhance interpretability, LIME analysis is applied to selected test samples, providing feature-level explanations and revealing the reasoning behind the model predictions.

4. EXPERIMENTAL RESULTS

This section presents the experimental results for four deep learning models: ANN, CNN, LST, and a hybrid architecture applied to the classification of power quality (PQ) disturbances. The models were trained and tested using a structured dataset containing key electrical and environmental features, and their performance was evaluated using accuracy, precision, recall, and F1-score to assess their capability in distinguishing normal conditions from various PQ anomalies.

Beyond quantitative evaluation, training and validation curves, confusion matrices, and LIME-based interpretability analyses were examined to assess learning behavior and prediction reliability. These complementary results enable a comparative analysis of learning efficiency, generalization performance, and interpretability for each model, highlighting the one that offers the most effective solution for real-time PQ monitoring in smart grid environments.

Figure 2 presents the skewness and kurtosis values for four key features in the PQ dataset: Voltage_Sag, Harmonics, Tempera-

ture, and Pollution_Level. Skewness values between -0.17 and 0.11 indicate that all features exhibit near-symmetric distributions, with only mild deviations in Voltage_Sag, Harmonics Pollution_Level, and an almost perfectly centered distribution for Temperature. Kurtosis values ranging from -0.22 to 0.15 similarly reflect mesokurtic, normal-like behavior, with no evidence of extreme outliers or unusually flat distributions. These results confirm the statistical soundness of the dataset and support the use of parametric machine learning models by contributing to stable training behavior and improved generalization.

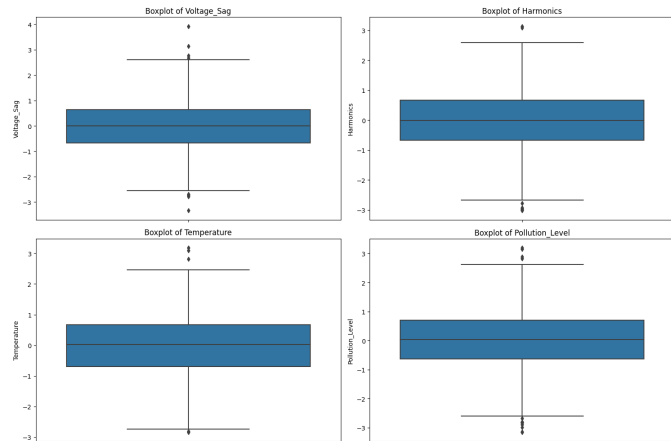


Fig. 2. Skewness and Kurtosis analysis of key features

Figure 3 presents the histogram and probability density plots for four key features: Voltage_Sag, Harmonics, Temperature, and Pollution_Level. All features exhibit approximately bell-shaped distributions, indicating near-normal behavior. Voltage_Sag and Harmonics show symmetric, centered profiles, while Temperature displays a slightly flatter curve consistent with its mild negative kurtosis. Pollution_Level also follows a normal-like distribution with slight left skewness and no significant outliers. The near-Gaussian nature of these features is beneficial for machine learning models that assume or perform better with normally distributed data, reducing overfitting risk and supporting stable training. Overall, these plots confirm that

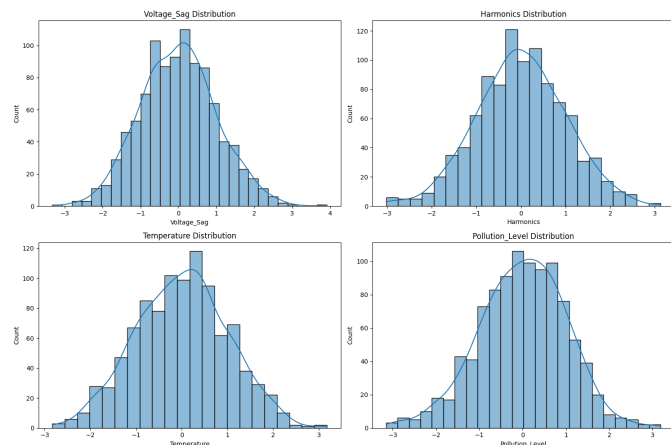


Fig. 3. Histogram distributions of selected features

the selected features are statistically well-behaved and suitable for direct use in supervised PQ classification pipelines.

Figure 4 presents the Pearson correlation matrix for the major features in the PQ dataset, illustrating the linear relationships between feature pairs. Most coefficients are close to zero, indicating minimal linear dependency. The strongest positive correlation appears between Harmonics and Reactive_Power_Compensation (≈ 0.06), while the weakest negative correlation is observed between Temperature and Voltage_Stability_Index (≈ -0.05), confirming that the features are largely independent.

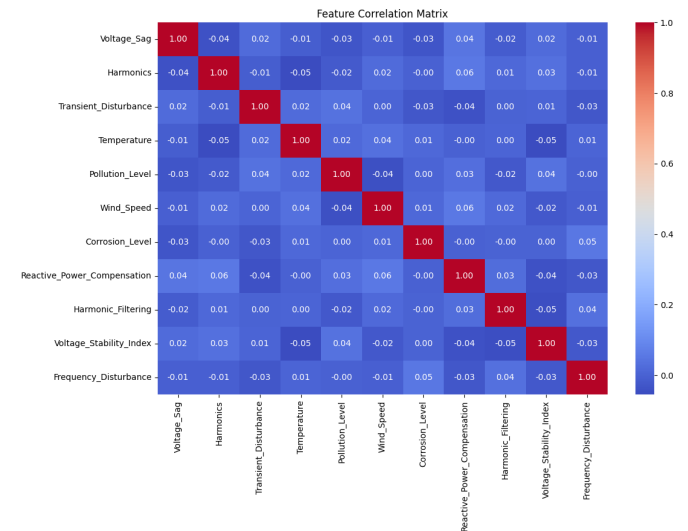


Fig. 4. Feature correlation matrix

This low level of multicollinearity is beneficial for models sensitive to feature redundancy, as it ensures that each variable provides distinct information for classification. Overall, the correlation structure demonstrates that the dataset is well-organized and that the selected features offer complementary insights, supporting stable training and strong generalization in smart grid and industrial monitoring applications.

Figure 5 presents the training and validation accuracy and loss curves for the ANN, CNN, LSTM, and hybrid models over 25 epochs, illustrating each architecture's learning behavior and convergence generalization capability. The ANN model (Fig. 5a) shows stable learning with closely aligned curves, although its final accuracy is slightly lower than that of the deeper models. The CNN model (Fig. 5b) converges more rapidly and achieves higher validation accuracy, reflecting effective spatial feature extraction. The LSTM model (Fig. 5c) reaches high accuracy but displays minor validation-loss fluctuations after epoch 15, indicating sensitivity to sequential noise. The Hybrid model (Fig. 5d) delivers the best overall performance, achieving near-perfect accuracy ($\sim 99.8\%$) and minimal loss with almost identical training and validation trajectories. These results confirm that combining spatial learning of CNN and temporal modeling of LSTM yields the most stable and accurate solution for PQ disturbance classification.

Figure 6 shows the confusion matrices for the ANN, CNN, LSTM, and hybrid models used in classifying power quality

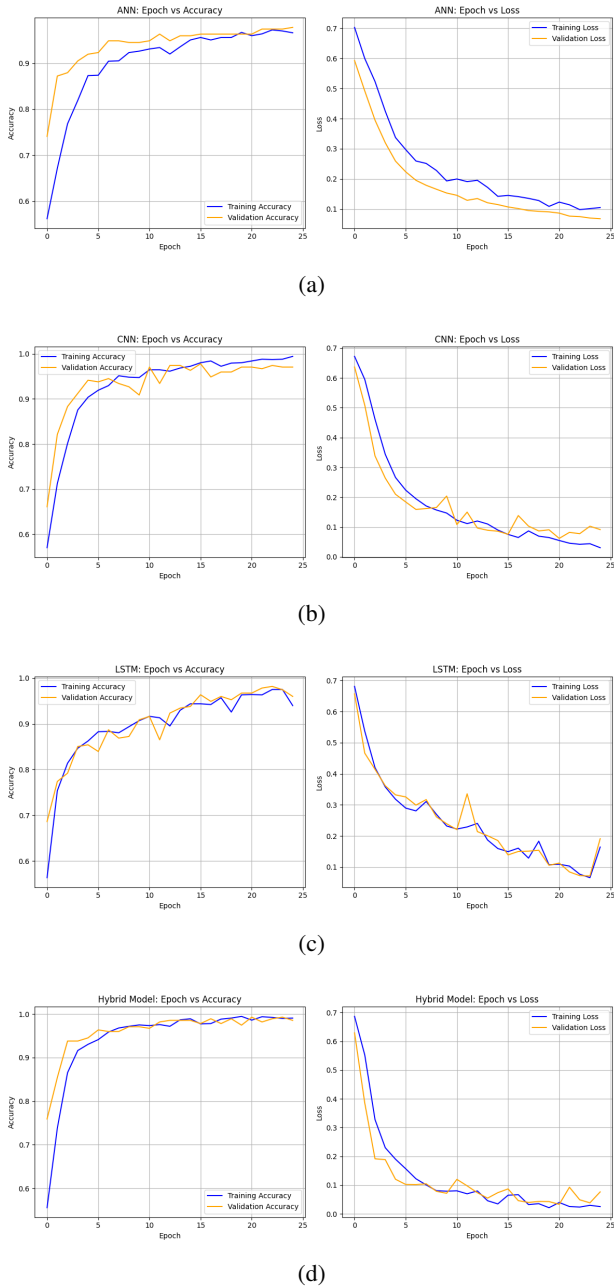


Fig. 5. Accuracy and loss trends across ANN, CNN, LSTM, and hybrid models

disturbances. All models correctly identify all PQ disturbances, with zero false negatives, demonstrating perfect sensitivity. The ANN model (Fig. 6a) achieves 133 true negatives and 137 true positives with only 4 false positives, while the CNN (Fig. 6b) and LSTM models (Fig. 6c) produce slightly more false positives (7 and 6, respectively) but maintain high recall. The hybrid model (Fig. 6d) delivers the strongest overall performance, achieving 134 true negatives and 137 true positives with only 3 false positives, representing the best balance between precision and specificity. Overall, while each model performs effectively, the Hybrid architecture provides the most reliable classification for real-time PQ monitoring.

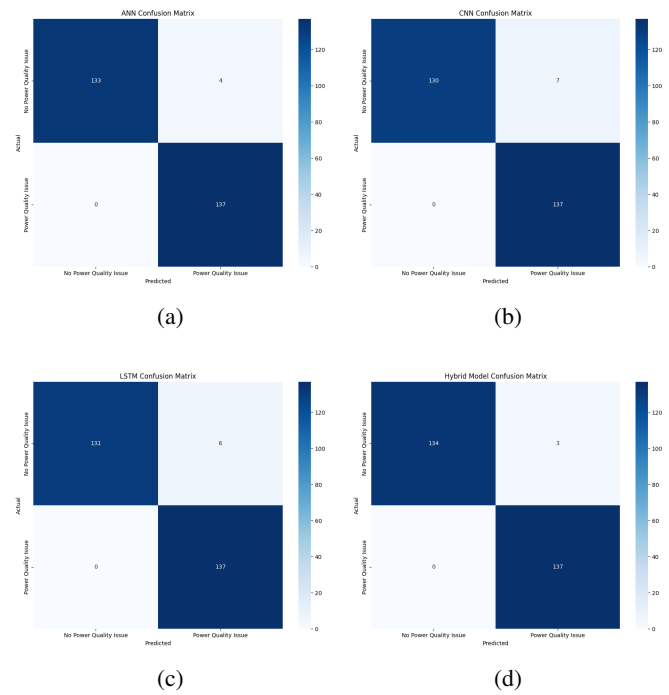


Fig. 6. Accuracy and loss trends across ANN, CNN, LSTM, and hybrid models

Figure 7 compares the performance of the ANN, CNN, LSTM, and hybrid models using accuracy, precision, recall, and F1-score. The ANN model (Fig. 7a) produces stable and well-balanced results across all metrics (≈ 0.985). The CNN model (Fig. 7b) shows slightly lower performance (accuracy: 0.9745, F1-score: 0.9744), mainly due to a minor reduction in recall. The LSTM model (Fig. 7c) improves on this with accuracy and

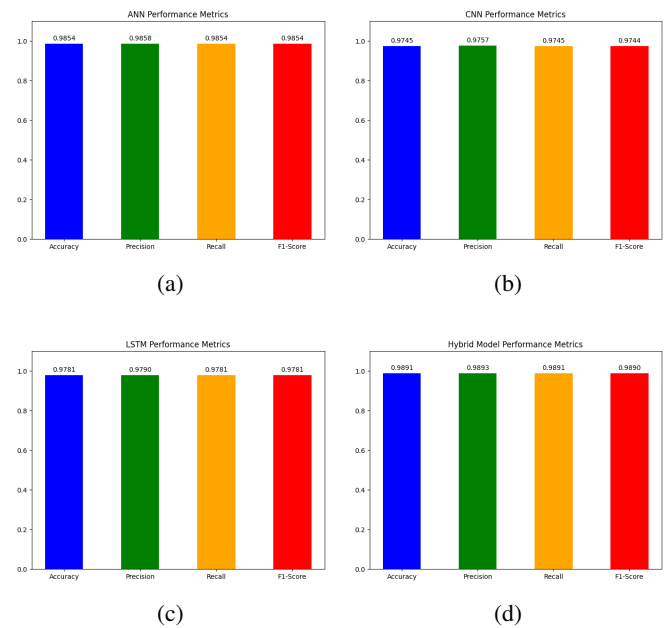


Fig. 7. Comparative performance metrics of ANN, CNN, LSTM, and hybrid models

F1-score values of approximately 0.9781, reflecting its strength in modeling temporal dependencies in PQ signals.

The hybrid model (Fig. 7d) achieves the highest scores across all metrics (accuracy: 0.9891, F1-score: 0.9890), demonstrating superior accuracy and generalization robustness. This advantage stems from the combined spatial learning capability of CNNs and the temporal modeling capacity of LSTMs. Overall, the hybrid architecture emerges as the most effective and reliable option for real-world PQ monitoring in intelligent grid systems.

Figure 8 presents LIME explanations for three representative samples in the power quality disturbance classification task, highlighting the most influential features contributing to each prediction. In Fig. 8a, Sample 83 is correctly predicted as “No Power Quality Issue,” with Harmonics acting as the strongest negative contributor, supported by features such as Voltage_Stability_Index and Frequency_Disturbance. This indicates that stable harmonic and voltage behavior are key indicators of nondisturbance conditions.

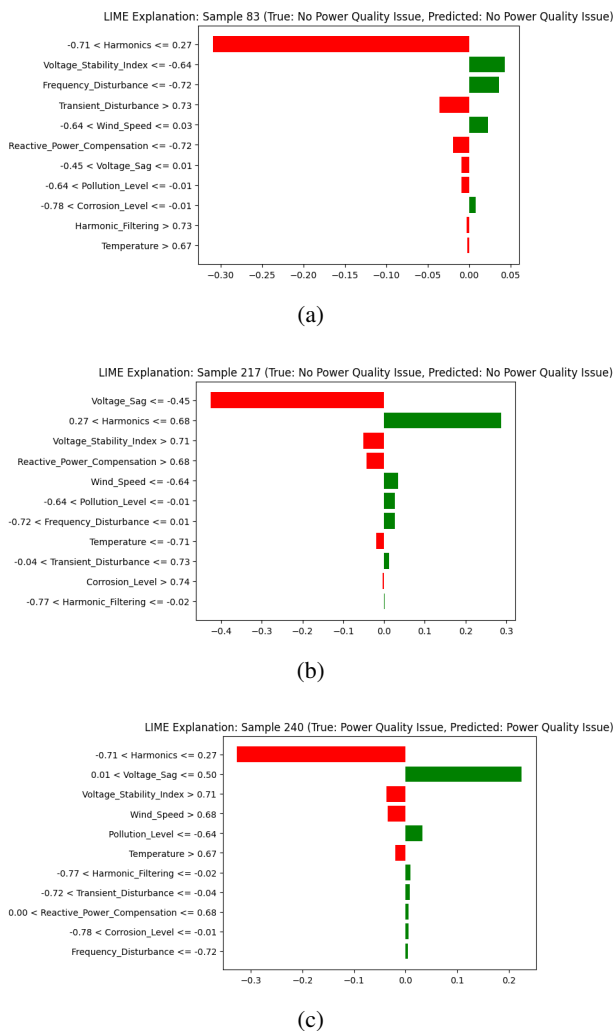


Fig. 8. LIME explanations for individual predictions

Figure 8b shows Sample 217, also classified as “No Power Quality Issue.” Here, Voltage_Sag is the dominant negative contributor, while Harmonics and Voltage_Stability_Index provide a mild positive influence, demonstrating LIME’s ability to capture subtle feature interactions even when contributions diverge.

In Fig. 8c, Sample 240 is correctly identified as a “Power Quality Issue,” driven primarily by strong positive contributions from Harmonics, along with supporting influences from Voltage_Sag and Wind_Speed. These features collectively indicate a genuine PQ disturbance.

Overall, the LIME explanations in Fig. 8 enhance the interpretability of the model by consistently highlighting critical features such as Harmonics, Voltage_Sag, and Voltage_Stability_Index. This strengthens user trust and supports practical deployment in real-world power system monitoring.

5. DISCUSSION

The results of this study confirm the strong effectiveness of deep learning methods, particularly the proposed hybrid architecture, in classifying PQ disturbances with high accuracy and reliability. As shown in Table 3, the standalone ANN, CNN, and LSTM models reached accuracies of 98.54%, 97.45%, 97.81%, respectively, demonstrating their ability to capture either spatial or temporal characteristics but also their limitations when these dependencies need to be modeled jointly. ANN provides fast and stable learning but lacks temporal sensitivity; CNN effectively extracts spatial features yet shows slightly lower recall; and LSTM models sequential patterns well but exhibits minor validation fluctuations and longer training times.

The Hybrid model, integrating both spatial and temporal feature learning, outperforms all standalone architectures with an accuracy of 98.91% and an F1-score of 98.90%. Table 3 positions these results within the broader literature, where prior CNN-, LSTM- attention-based approaches [9, 10, 17] demonstrate strong performance but often lack explainability or rigorous statistical validation. Given differences in datasets and evaluation protocols, cross-study comparisons remain indicative rather than definitive, making the held-out test set evaluation the most reliable measure of model performance.

Table 3

Comparison of the proposed method with recent studies

Study [Ref]	Model	Accuracy	F1-score
[9]	Ensemble CNN (ECNN)	98.76%	–
[10]	CNN + Bi-LSTM	98.54%	98.51%
[11]	CNN + Adversarial defense	97.10%	96.80%
[12]	Bayesian CNN	97.80%	97.50%
[14]	Hybrid 1D-2D CNN	98.30%	98.20%
[16]	CNN-GRU	98.65%	98.60%
[15]	CNN-LSTM	98.72%	98.69%
[17]	CNN-AD (Atomic decomposition)	97.90%	97.70%
Proposed study	Hybrid + LIME	98.91%	98.90%

Distinct from earlier work, this study pairs high predictive accuracy with explainable AI and comprehensive statistical preprocessing, including skewness and kurtosis correlation analysis to ensure data integrity and feature independence. The hybrid architecture, combined with LIME-based interpretability and robust preprocessing, enhances scientific rigor and establishes the proposed model as a promising candidate for real-time power quality monitoring in smart grid environments.

6. LIMITATIONS AND FUTURE WORK

Despite the strong performance of the Hybrid model, several limitations remain. First, its robustness under challenging conditions such as severe missingness, sensor drift, or distributional shift was not explicitly evaluated; future work will integrate uncertainty-aware imputation and drift detection mechanisms. Second, broader generalization across grids with varying disturbance taxonomies, sampling configurations, and environmental conditions requires multi-site validation and cross-dataset experimentation. Third, while LIME offered valuable instance-level interpretability, incorporating global explanation methods and counterfactual analysis could further enhance transparency and diagnostic utility. Lastly, real-time deployment aspects such as latency, memory footprint, and on-device inference were not optimized; subsequent research will focus on lightweight architectures and online adaptation to support field-ready, safety-critical applications.

7. CONCLUSIONS

This study introduced a deep learning-based framework for classifying PQ disturbances using ANN, CNN, LSTM, and a hybrid architecture. The hybrid model achieved the best performance, with 98.91% accuracy and a 98.90% F1-score, demonstrating its effectiveness in capturing both spatial and temporal characteristics of PQ signals. The integration of LIME enhanced interpretability by identifying the most influential features behind each prediction, supporting transparency and trust in AI-assisted power system diagnostics. Comprehensive statistical analyses, including skewness and kurtosis, validated data quality and contributed to model robustness. Comparison with recent studies further showed that the proposed model is competitive while offering added strengths in explainability and preprocessing rigor.

The findings indicate that hybrid and interpretable AI approaches are promising for intelligent PQ monitoring in smart grid environments. Future work may focus on real-time deployment challenges, handling unbalanced datasets, exploring transfer learning, or unsupervised methods to improve adaptability across diverse grid configurations. Overall, this study provides a scalable, accurate, and explainable solution for modern power system diagnostics.

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