STFT-ENGB: A Hybrid Time Frequency and Gradient Boosting Approach for Power Quality Disturbance Detection

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Power signal processing is a specialized domain within signal processing that focuses on the analysis, interpretation, and manipulation of signals in electrical power systems. In modern smart grids, Power Quality Disturbances (PQDs) can result in considerable operational disruptions and financial losses for energy stakeholders. This research introduces a Short-Time Fourier Transform fused Efficient Natural Gradient Boosting (STFT-ENGB) model for robust recognition of power quality disturbances with energy grid applications. A comprehensive framework used for PQD identification by leveraging advanced power signal processing techniques and time-frequency-based feature extraction. The system collects electrical measurements from the power system includes voltage and current. The Z-score normalization is a preprocessing technique for reducing noise. The STFT is utilized to extract discriminative, time-localized features from the power signals. These extracted features are then combined using a late fusion strategy to form a unified representation. The proposed method was implemented using Python 3.10.1. Extensive experiments demonstrate that the proposed STFT-ENGB approach performs better than multimodal baseline architectures, achieving superior results, with accuracy, F1-score, recall, and precision ranging from 95% to 99%. These findings offer a promising solution for real-time power signal monitoring in smart grid environments, facilitating intelligent fault diagnosis and improving the overall resilience and responsiveness of modern electrical infrastructure.

Povzetek: Predstavljen je hibridni model STFT-ENGB, ki združuje časovno-frekvenčno analizo in izboljšano gradientno pospeševanje za zaznavanje motenj kakovosti električne energije. Z normalizacijo, STFT-izločanjem značilk in pozno fuzijo doseže dorbo napovedljivost ter omogoča zanesljivo diagnostiko v pametnih omrežjih.

1 Introduction

Power signal processing is a crucial field in electrical engineering that is important for many applications, including effective energy management, defect detection in electrical grids, and power quality assessment [1]. The complexity of electrical infrastructure has raised the need for high-performance algorithms for power signal evaluation. Such systems require precise, accurate, efficient power signal processing systems to both enhance system reliability and enhance anomaly detection [2]. Time-frequency analysis (TFA) has proved to be an effective technique for signal representation and feature extraction, since the conventional signal processing techniques did not consider the non-stationary nature of power signals. TFA is an integrated method of analyzing non-stationary power signals that fluctuate over time, combining frequency-domain and time-domain analyses [3]. Conventional methods tend not to be able for extract useful information from non-stationary signals, particularly in power systems where the signal suffers from noise, transients, harmonics, and the occurrence of other abnormalities [4]. These methods have improved feature recognition and system malfunction detection of power data, particularly significant for system performance and operational security. Most typical power signal features include noise, transients, and harmonics that can indicate some form of overall system malfunction due to faulty equipment or power quality issues [5]. Using the features present in power signals, it becomes possible to digitalize monitoring, fault detection and diagnosis, preventive maintenance, and system operation assessment. By extracting features from power data efficiently, the system has tremendous potential to realize the efficiencies available for quickly identifying potential systematic issues before they develop into issues of greater consequence [6]. More specifically, TFA techniques can enable more accurate identification of harmonic distortion, frequency variations, and abrupt voltage transitions acquired from measurements. These techniques can also potentially provide more substantial diagnoses, improving the power system performance and reliability [7]. Power signal processing can greatly improve electrical grid and microgrid monitoring and control, particularly as the electrical grids become more renewable energy - Smart grids. The systems can provide more fault location, energy management, and predictive maintenance strategies to enhance both reliability and performance in the case of comprehensive feature identification [8, 9]. This research aims to create a new power signal processing method for TFA that successfully extracts features. By addressing the challenges of dynamic and non-stationary power signals, the method should achieve high accuracy for detecting abnormalities, transient phenomena, and failures in systems. [10]. The difficulty is to find a compromise between time resolution and frequency resolution, a common drawback of TFA methods. Finding balance depends on the preservation of algorithm performance in power system applications [11]. The formal research question was stated as follows;

How does the incorporation of the ENGB model increase the classification accuracy and computational lightness of PQD classification by conventional classifiers?

In What ways the STFT used for feature extraction to discriminate among different types of power quality disturbances in three-phase electrical systems?

How suitable the PQD detection model used to generalize various datasets and industrial conditions for different operating conditions and noise rates?

The objective of this research is to create a revolutionary Short-Time Fourier Transform fused Efficient Natural Gradient Boosting (STFT-ENGB) approach to enhance power quality disturbances with energy grid applications. The suggested approach enhances the detection of PQDs in low SNR conditions using hybrid spectral and probabilistic modeling. The key contributions of this research as follows,

Dataset Collection: A three-phase power quality event dataset was collected from Kaggle, it contains synchronized voltage and current signals across multiple disturbance classes.

Data Pre-Processing and Feature Extraction: The time-frequency analysis, Z-score normalization techniques used as preprocessing stages to normalize the data, which makes it ideal for smart grid applications.

Optimized Classification Model: An STFT-ENGB model used for identifying PQDs in a robust manner that improves smart grid system reliability.

Real-Time Results: The simulation results evaluate the precision, accuracy, recall, and F1 score for optimizing the smart grid with less computation utility.

The research structure is outlined as follows: The literature review section analyzes to provide background for the inquiry. The materials and methods section describes the data collection and analysis. Summarizes the findings, emphasizing critical findings in this section, provides a complete interpretation of the data, the concludes with an overview of the research's ramifications and future directions.

2 Related work

The relevant literature explores AI-driven power quality disturbance detection systems, focusing on adaptive boosting models, and intelligent data acquisition to enhance real-time fault recognition, computational efficiency, feature discriminability, and overall grid reliability in smart energy environments.

The method for converting a microwave frequency measuring system for utilizing TF into a TFA [12]. It also has two TFA relationships: parallel stimulated Brillouin scattering (SBS) for microwave TFA, and time-division SBS for TFA with great specificity for periodic signals. Simulations show how the system can be reconfigured in multiple dimensions. Fault diagnostics in rolling bearings are critical for forecasting damage and minimizing financial losses [13]. A multi-rolling component fault identification approach integrates the time-frequency analysis and a vibration signal produced by multi-curve extraction techniques, thereby improving weak periodic fault impulses and finding homologous defects. The experiments conducted show that TF separation (TFS) and identification are effective. STFT-based approaches are inadequate for processing non-stationary signal data in fluctuating operational environments [14]. TFA technique enhances instantaneous frequency (IF) curves by increasing initial frequency and using a synchro squeezing operator, improving time-frequency accessibility and feature extraction capability. Table 1 presents a summary of related work on power quality disturbance detection.

Table 1: A summary of related work on the power quality disturbance detection

Ref	Technology Used	Objective	Result	Challenges
[15]	Time-Frequency Analysis (TFA)	To assess power quality affected by nonlinear loads due to power electronics-based renewables	Identified the need of TFA methods to analyze time-dependent waveforms	Time-varying voltage and current waveforms complicate reliable power quality assessment
[16]	Convolutional Neural Network (CNN)	To detect and monitor health conditions like epilepsy using EEG signals	Achieved high accuracy, precision, recall, and F1-score using 3570 EEG signal pairs	Effective integration of multiple TFA approaches in biomedical signal processing was a challenge
[17]	TF Self-Similarity Enhancement Network (TFSSEN): includes adaptive TF characterization, attention residual group, mixed-scale TFA	To identify mechanical issues in nonstationary signals from wind turbines	Improved detection accuracy for mechanical problems using enhanced TF features	Complexity in analyzing nonstationary signals and combining global/local attention mechanisms
[18]	Deep learning, transfer learning	To improve efficiency and accuracy in detecting and identifying bolt defects	Detection accuracy improved	Required algorithm optimization for better accuracy
[19]	LPSVM (Least Squares Support Vector Machine),	To reduce computational cost; and performance of SVM	Proposed model achieved 0.40 times the computational cost	Kernel complexity increases the computational load;
[20]	Interactive robot model, machine learning, signal processing, electric energy metering system	To enhance power quality monitoring and prediction under overload conditions	Achieved ideal prediction accuracy without sacrificing speed;	Conventional methods didn't meet accuracy expectations;

3 Problem statement

The challenge in several domains, including power systems and fault diagnosis is to process nonstationary signals, such as ECGs, vibration signals, and wind turbine signals more effectively, by using TFA techniques [13]. Most existing TFA works have some form of the limitations including noise sensitivity, low resolution, and impediments in process time-varying signals. More sophisticated techniques that can further facilitate signal reconstruction and accuracy for detection while leveraging even more advanced abilities for feature extraction are needed. TFA methods might not sensitive enough to measure quickly, and the nonlinear nature of waveforms caused by power electronics-based renewable sources [15]. These techniques were frequently sensitive or flexible and it was desirable to observe faint or temporary perturbations in different loading conditions. To overcome these limitations, the suggested STFT-ENGB approach, incorporate adaptive noise reduction techniques for improved input data quality, providing better performance robustness. The algorithm employs real-time feature extraction using STFT to minimize computational burdens and capture dynamic changes effectively. The flexibility in STFT-ENGB makes it possible to fine-tune and verify it for a variety of power systems and operating regimes.

3.1 Methodology

The previous section reviewed recent studies on power quality disturbance detection. These studies highlighted shortcomings in computational efficiency, real-time responsiveness, and adaptive data acquisition, and the proposed model explained the research gap to address these issues.

The approach combines several advanced signal processing methods for power quality event analysis. It applies Z-score normalization for data standardization, STFT for feature extraction, and ENGB for better feature extraction. The combined STFT-ENGB association improves the resilience and precision of power signal analysis, particularly in fault recognition and categorization. The hybrid approach maximizes signal processing by reducing and enhancing feature extraction. Figure 1 depicts the methodological flow for the system under consideration.

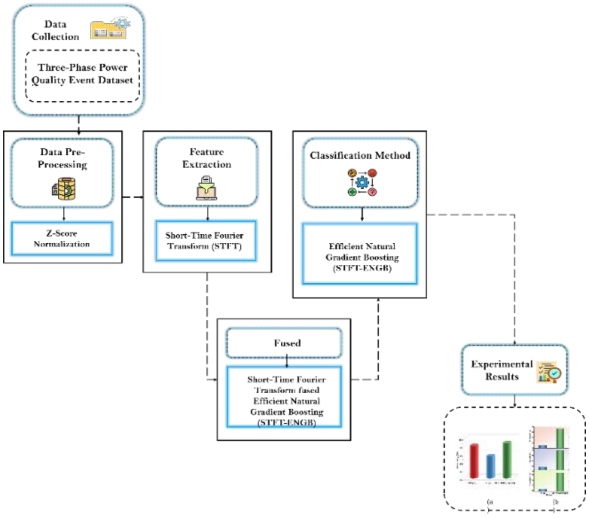

Figure 1: Flow of the recommended system for the proposed methodology

3.2 Data gathering

The power quality event dataset was gathered from the open-source Kaggle website https://www.kaggle.com/datasets/zoya77/three-phase-power-quality-event-dataset. The dataset provides electricity measurements from a three-phase power supply gathered throughout time. The dataset consists of 100 samples per class, total of about 600 recordings. Each signal has a 3-phase voltage and current waveform, with around 10 cycle's duration. It includes 6 event classes like voltage sag, swell, interruption, harmonics, flicker, and normal operation. The dataset was divided into training and testing samples, where the training samples have (70%) and the testing samples has (30%). Since the dataset was class-balanced with approximately 100 samples per class, no additional imbalance handling techniques like oversampling or class weighting were required. It was especially appropriate in the design and validation of classification models, fault detectors, and signal-processing algorithms in smart grids. The information contained in the dataset used to analyze the power distributions. The given dataset was capable to fully assist the purpose of creating a trustworthy real-time PQD detection system.

3.3 Data exploration

Figure 2 illustrates the feature importance analysis of power signal processing via TFA. The features, such as voltage and current phases of the three phases (A, B, C), are ordered according to the impact on the analysis. Voltage_phase_a, voltage_phase_b, and voltage_phase_c is of greater importance, indicating that the voltage signals of different phases play an important role in the analysis. The existing features, like current_phase_a, current_phase_b, and current_phase_c, possess relatively lesser importance. This emphasizes the significance of voltage signals in the time-frequency feature extraction process for STFT-ENGB.

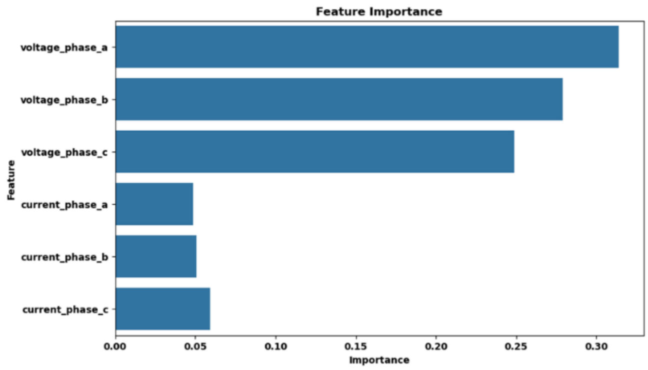

Figure 2: Feature Importance of power signal phases based on TFA

3.4 Z-score normalization using preprocessing technique

Normalization is essential when the preprocessing step, in particular while dealing with numerical characteristics in datasets linked to power signal processing and TFA. This method alters an intersection to maintain uniformity across changed features. Z-score standardization was used to normalize the various response variables, including power consumption signals and measurements of system performance. This method supports TFA-based anomaly detection, as it allows the information analyzed by the system to be altered from the original value to a normalized form such that the mean value is 0 and the standard deviation is 1. The formula for Z-score normalization is presented in Formula (1).

$$x' = \frac{x_j - G_j}{\text{std}\,(G)} \quad (1)$$

x^' = Normalization value results, x = The attribute's value that has to be normalized, G_j = The attribute's mean value, and std (G) = Attribute G for the standard deviation. Table 2 represents the output of Z-Score normalization.

Table 2: Output of Z-score normalization

voltage_phase_a	**voltage_phase_b**	**voltage_phase_c**	**current_phase_a**	**current_phase_b**	**current_phase_c**
-0.00	0.17	-0.15	0.06	1.15	-1.21
0.09	0.09	-0.16	0.79	0.50	-1.42
0.16	-0.02	-0.11	1.22	-0.20	-0.97
0.18	-0.15	-0.05	1.25	-1.08	-0.41
0.10	-0.18	0.10	0.80	-1.31	0.50
0.01	-0.17	0.18	-0.02	-1.08	1.16
-0.10	-0.05	0.16	-0.65	-0.57	1.44
-0.18	0.04	0.10	-1.36	0.39	1.08
-0.16	0.15	0.05	-1.35	0.95	0.28
-0.11	0.23	-0.09	-0.75	1.42	-0.60

3.5 Feature extraction using Short-Time Fourier Transform (STFT)

STFT provides a fixed time-frequency resolution which is predictable and simpler to be implemented in any practical setting of grid monitoring. Furthermore, a proper choice between the window functions and lengths, the consequences of spectral leakage in STFT. The SIFT was capable of uniformly sampling localized transient events with reduced processing requirements makes it an appealing option to the suggested power quality disturbance detection system. The STFT is an influential signal processing technique that partitions signals into short, overlapping segments and applies the STFT to each segment. This way it analyzes a signal's frequency and time characteristics, which is ideal for non-stationary signals by changing characteristics over time. An STFT produces a time-frequency image that presents the energy content in the signal as a function of time and frequency. STFTs are typically used in power signal processing to produce a time-frequency image that can be interpreted to identify certain characteristics by looking for patterns in the frequency domain. It is necessary for a wide range of functions, from fault detection to classification of signal classification. STFTs can be found in a multitude of applications, including speech processing, biomedical signal analysis, and industrial monitoring.

An STFT on discrete-time, periodic signals in power signal processing, which often does not get the expected result of frequency response due to spectral leakage. Spectral leakage occurs because the energy of the signal spreads out across the frequency spectrum. When a finite segment of a signal is analyzed using a Fourier transform, the boundaries create discontinuities, causing the energy of that signal segment to be spread in the frequency domain. A signal's periodic extension can be misleading to the discontinuities punctuating the period, causing errors in its frequency representation. Given the role of spectral leakage in extracting features and analyzing power signals, it's important to understand and manage the error source, especially when analyzing signals in the time-frequency domain.

The functions are vital in power signal processing for analyzing discrete-time signals and reducing spectral or frequency leaking that occurs because of signal discontinuities that ensue at the limitations of data segments. Most electrical component functions decay to zero at the edges, accordingly to these window functions' properties, overlapping power signals should be used to not interfering with the data loss that occurs. To calculate the STFT of a discrete-time signal w(m), a window function x(m) is applied to each segment, and its frequency content is analyzed between time intervals. The STFT Formula (2) is given by:

$$\text{STFT}(m, l) = \sum_{m=0}^{M-1} w(m)x(m - nG)d^{-i\frac{2\pi}{M}lm} \quad (2)$$

When m is the sample index, l the frequency index, M the window length, x(m) the power signal function, n the power signal location, and G the hop size between consecutive electrical component systems. This is required for accurate feature extraction and time-frequency analysis in power applications that use signal processing.

3.6 Late fusion strategy

Late fusion strategy describes the combining outputs process of high-level feature representations from multiple modalities, after each modality has been processed independently through extracted features. The modalities were independently classified by using this approach, which constitutes the characteristics of each modality. Every modality was classified separately when the attributes had been integrated. This method has the benefit that each modality might learn its features by using the classifier. Vectors were then fused to generate the multimodal representation on equation (3), which conveyed a weighted combination. Where, F represents the attention modules.

$$F=\text{Fusion}\ (A,V) \quad (3)$$

3.7 Efficient natural gradient boosting (ENGB)

The ENGB classifier using the electrical component for TFA in power signal processing relies on accurate feature extraction from complicated information. The ENGB model was used to increase its flexibility of variables' time-frequency representation exemplified by STFT. In specific, the losses will be customized to deal more adequately with the issue of class imbalance, and mechanisms of weighting features were integrated to draw more weight on transient-sensitive features. The ENGB model's hyperparameters were tuned by STFT. The associated notions and computation of time-frequency distributions are highly complicated, posing obstacles for use in practical engineering applications. The enhanced approach to generating TFA features establishes a connection between conventional signal processing approaches and TFA, utilizing sophisticated mathematical approaches. A scoring function T(θ,z_j) is calculated using Shannon information from signal characteristics subscripts 〖z〗_j, followed by Formula (4).

$$T(\theta, z_j) = -logO_\theta(z_j) \quad (4)$$

When O_θ (z_j) is the probability value of z_j, and θ is the characteristic vector of the prediction distribution. Let -logO_θ (z_j) = e (θ) and accomplish a Taylor expansion on e (θ + c '). The third- and higher-level terms have been eliminated to simplify the calculation using Formula (5).

$$e(\theta + c') = f(\theta) + c'^S \frac{\partial e(\theta)}{\theta} + \frac{1}{2} c'^S \frac{\partial e(\theta)}{\theta} \left(\frac{\partial e(\theta)}{\theta}\right)^S c' \quad (5)$$

Where, e(θ) indicates the error function, and c' depicts the transpose vector; ∇̃ it represents the ENGB. Convert the Euclidean space to a statistical manifold, and utilize Formula (6) to extract signal features:

$$C_{LK} = \int_{-\infty}^{+\infty} O_\theta(z_s) * (e(\theta + c') - e(\theta)c(z_s) = \int_{-\infty}^{+\infty} O_\theta (z_s) * \left(c'^S \frac{\partial e(\theta)}{\theta} + \frac{1}{2} c'^S \frac{\partial e(\theta)}{\theta} \left(\frac{\partial e(\theta)}{\theta}\right)^S c'\right) c(z_s) \quad (6)$$

Following the integral calculation rule, Formula (7) can be divided into two portions for separate calculations. The first portion is simplified as:

$$\int_{-\infty}^{+\infty} O_\theta(z_s) * \left(c'^S \frac{\partial e(\theta)}{\theta}\right) c(z_s) = \left(c'^S \frac{\partial e(\theta)}{\theta}\right) * O_\theta (z_s) \int_{-\infty}^{+\infty} O_\theta(z_s) c(z_s) \quad (7)$$

The second part could potentially be expressed as Formula (8):

$$C_{LK} = \int_{-\infty}^{+\infty} O_\theta(z_s) * \left(c'^S \frac{\partial e(\theta)}{\theta} + \frac{1}{2} c'^S \frac{\partial e(\theta)}{\theta} \left(\frac{\partial e(\theta)}{\theta}\right)^S c'\right) c(z_s) = \frac{1}{2} c'^S * \int_{-\infty}^{+\infty} O_\theta (z_s) * \left(\frac{1}{2} c'^S \frac{\partial e(\theta)}{\theta} \left(\frac{\partial e(\theta)}{\theta}\right)^S\right) c(z_s) *= c' \frac{1}{2} c'^S \psi(\theta) c' \quad (8)$$

The Riemann metric of the statistical manifold at θ is $\psi(\theta)$, which characterizes the Fisher details received from $O_\theta(z_s)$, using Formula (9).

$$\psi(\theta) = \mathrm{F}_z r\mathrm{O} \left[\nabla \mathrm{T}(\theta, z_j) \nabla \mathrm{T}(\theta, z_j)^S\right] \quad (9)$$

The natural gradient $\tilde{\nabla} T(\theta, z_j)$ can be estimated using the general ENGB as follows, by Formula (10):

$$\tilde{\nabla} T(\theta, z_j) = \psi(\theta)^{-1} \nabla \mathrm{T}(\theta, z_j) \quad (10)$$

This strategy improves signal feature extraction through TFA by using the ENGB technique, which aligns the Euclidean gradient with the statistical manifold of signal occurrences. To develop an enhanced technique for power signal processing based on TFA in the different phases below. Use θ^0 as the initial parameter vector for signal characteristics. Generate the signal feature z_j and its accompanying parameter vector θ_s^{n-1} iusing the ordinary gradient in the n^{th} iteration. To upgrade the parameter vector, determine the natural gradient $\tilde{\nabla} T\ (\theta_s^{n-1}, z_j)$ and, build a different set of base learners along this gradient. The update rule for parameters were expressed in equation (11):

$$\theta = \theta^0 - \beta \sum_{n=1}^{N} \alpha^n \beta^n \quad (11)$$

Here, θ^0 indicates the initial model parameters, and β represents the global learning rate. In the context of power signal processing, while the general procedure of power signal fluctuations is non-Gaussian, the suggests that each sample point should follow an electrical power system.

3.8 Short-time Fourier transform fused efficient natural gradient boosting (STFT-ENGB)

The STFT-ENGB hybrid is an integration of the STFT with TFA and ENGB to improve feature extraction in power signal processing. STFT segments signal to overlapping windows for comprehensive frequency and temporal analysis, whereas ENGB maximizes the extraction of signal features by matching gradients with the statistical manifold. The STFT-ENGB model achieves better signal processing strength, particularly when dealing with involved, non-stationary power signals. STFT-ENGB hybrid method used to perform better PQD because it uses both time-frequency analysis and machine learning models. STFT is the time-varying and localized characteristic of non-stationary power signals, hence appropriate when tracking transient and dynamic disturbances. ENGB increases the accuracy of the classification process by dealing with the non-linear and intricate patterns of the features. This combination guarantees a high detection rate, resistance to noises and applicability to different kinds of PQD. Moreover, the hybrid model was computationally efficient to allow monitoring in real time of the smart grid environment. Algorithm 1 shows the proposed STFT-ENGB model working procedure.

Algorithm 1: STFT-ENGB

```
import numpy as np
import pandas as pd
import scipy.signal as signal

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler
from lightgbm import LGBMClassifier

from sklearn.metrics import classification_report
X_signals = np.load("signals.npy")
y_labels = np.load("labels.npy")
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_signals)
def extract_stft_features(signal_data):
  features = []
  for sig in signal_data:
    f, t, Zxx = signal.stft(sig, nperseg = 128)
    power = np.abs(Zxx) ** 2
    mean_power = power.mean(axis = 1)
    features.append(mean_power)
  return np.array(features)
X_features = extract_stft_features(X_scaled)
X_train, X_test, y_train, y_test = train_test_split(
  X_features, y_labels, test_size = 0.2, stratify =
y_labels, random_state = 42)
model = LGBMClassifier(boosting_type =
'gbdt', n_estimators = 100)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
print(classification_report(y_test, y_pred))
```

4 Results

The proposed model's strategy and its applications in enhancing power quality monitoring through the integration of STFT-ENGB were described previously. This model effectively addresses disturbance detection by leveraging time-frequency feature extraction and adaptive boosting, offering a robust and real-time approach tailored to dynamic grid signal variations.

4.1 Experimental configuration

The system configurations with Python setups are employed for TFA is used to process power signals and extract features. The signal-piloted gain device acts as a triggering device which continuously checks the incoming power signals as per the occurrence of anomalies. It also triggers feature extraction and data acquisition when it recognizes an unusual variation in the regular activities. It was useful for avoiding the unnecessary data and efficiency of computation. Figure3 represents the Signal-Piloted Gain Device of Voltage Phase.

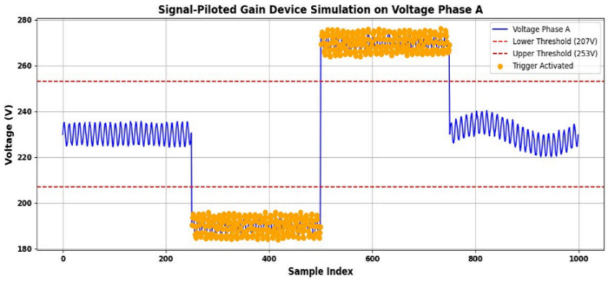

Figure 3: Signal-piloted gain device of voltage phase

The process can be implemented with a light-weight embedded microcontroller or digital signal processor

(DSP) and programmed with threshold-based detection algorithms. Hardware/software details was illustrated in Table 3.

Table 3: Hardware-software configuration for power signal detection

Component	Type	Details
Hardware Platform	Microcontroller / DSP	ARM Cortex-M series / DSP for real-time signal processing
Signal Input Interface	ADC (Analog-to-Digital Converter)	16-bit, high-speed ADC for sampling voltage and current waveforms
Triggering Logic	Comparator/Threshold Detector	Monitors signal amplitude/frequency changes to detect disturbances
Feature Extraction	Signal Processing Library	STFT implementation via CMSIS-DSP or similar optimized math libraries

4.2 Confusion matrix in power signal processing and feature extraction

Figure 4 depicts the confusion matrix for measuring the classification accuracy of a power signal processing model based on TFA. It indicates how accurately the model classifies four different classes, as labeled rows (True labels) and columns (Predicted labels). The diagonal values (74, 75, 75, and 69) represent the count of correct predictions for each class, which signifies that the model classifies with high accuracy. Where x – plane indicates the predicted label and y- plane indicates the True label. It was particularly useful for imbalanced datasets, where simple accuracy might be misleading. It assists in figuring out the model's operational efficiency and potential areas for improvement.

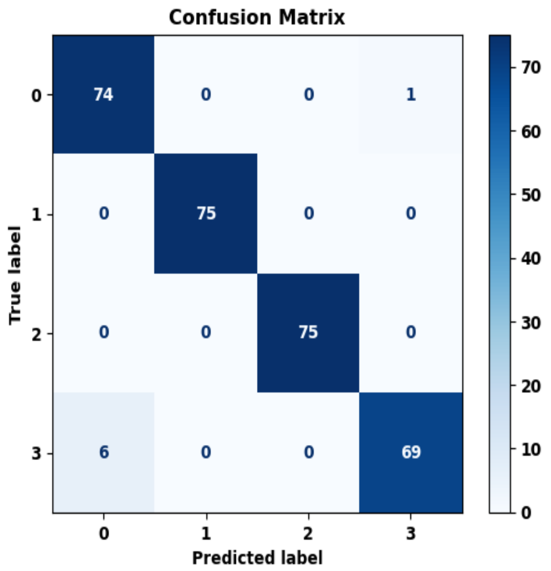

Figure 4: Confusion matrix showing classification performance for power signal processing using TFA

4.3 Current distribution and TFA across phases and classes in power signal processing

The analysis of the time series and distribution of current in Phase A among classes, emphasizes central predisposition and variability uniformity, as well as differences in oscillations between classes and phases. These characteristics are essential for power signal processing with TFA for efficient classification of different behaviors performed in STFT-ENGB.

4.3.1 Voltage distribution and TFA across classes in power signal processing using TFA

The voltage pattern and time series analysis of Phase A for varying classes show marked differences in the values of voltages, each with a distinct pattern for different classes. Such amplitude and phase differences are significant for feature extraction in power signal processing with TFA to discriminate operational conditions.

4.3.2 Voltage phase a distribution by class

Figure5 shows the distribution of voltage values for Phase A within four classes, which represent the IQR, with the median voltage value represented. This demonstrates that the different voltage values appear to vary widely across the classes. As an example, class 0 and class 1 appear to yield voltage values that are mainly between 220V and 240V. Here, the x- axis indicates the class label ranges from 0 to 3, and the y- axis illustrates the voltage (V) ranges from $180V$ to $280V$. It is important to recognize that the difference in voltage across the classes is important to differentiate between different operational states or behaviors, when the power signal processing model STFT-ENGB is based on TFA.

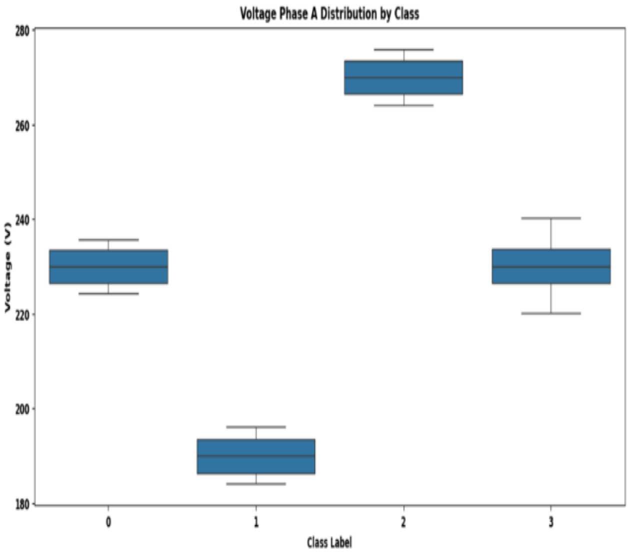

Figure 5: Voltage phase distribution across different classes in power signal processing using TFA

4.3.3 Voltage time series for each phase and class

Figure 6 shows the time series voltage for each phase (A, B, and C) in four classes (0 to 3) for the first 500 samples. Here, the $x-$ plane illustrates the sample index, and y-plane indicates the voltage (V), ranges from $180V$ to $280V$. Each coloured line represents a class, and the oscillating patterns of voltage are noticeable across the three phases. Where, blue line depicts class 0, orange line indicates the class 1, green line depicts the class 2 and red line represents the class 3. The differences in voltage values in time across phases and classes can be leveraged for feature extraction from power signals using TFA, which can distinguish distinct operational states or operational behaviors, STFT-ENGB, depending on voltage discrepancies.

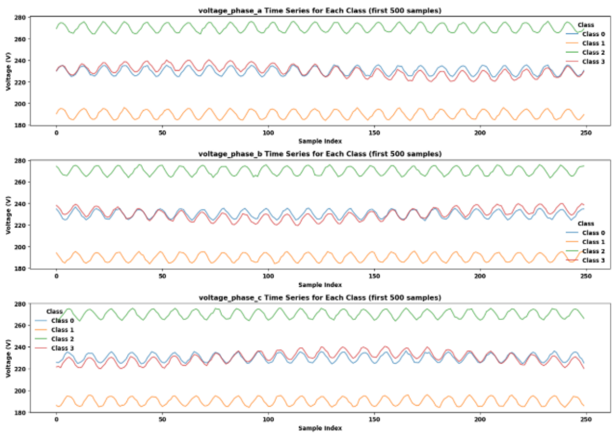

Figure 6: Voltage time series for each phase and class in power signal processing TFA

4.3.4 Current phase a distribution by class

Figure 7 presents the distribution of the current (in amperes, A) in Phase A, partitioned into four class labels. The interquartile range (IQR) is represented by each box, with the value of the median. This indicates that the central tendency and variability of the current values are fairly uniform between the classes. Where x –plane depicts the class label ranges from 0 to 3, and y- plane depicts the current in ampere (A), ranging from $8.5A$ to $11.5A$. This indicates that the central tendency and variability of the current values are fairly uniform between the classes. The data range, and there are no outliers, based on this analysis, the current in Phase A has comparable features for different classes and can be considered an important feature for the power signal processing model.

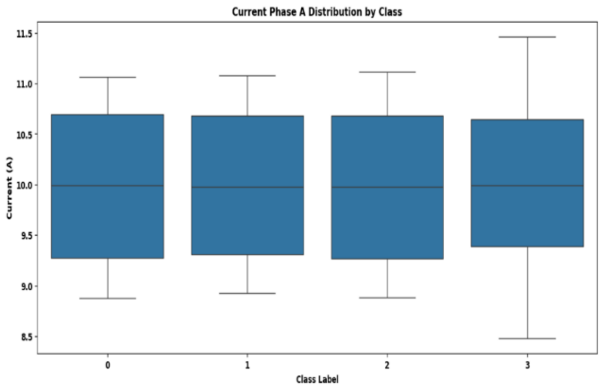

Figure 7: Distribution of current phase by the class label in power signal processing using TFA

4.3.5 Current time series for each phase and class

Figure 8 shows the existing time series for three phases (A, B, and C) of every class (0 to 3) using the first 500 samples. The time series of every phase is plotted separately, and every class is shown; the oscillations in the current are well apparent across all phases, and the amplitude and phase are slightly different between classes. The current phases a, band c was illustrated in Figure5. Here, the $x-$ plane indicates the sample size, and y- plane indicates the current in ampere (A), ranges from $8.5A$ to $11.5A$. Where, blue line depicts the class 0, orange line indicates the class 1, green line represents the class 2 and red line represents the class 3. The TFA strategy can be employed to derive meaningful features distinguishing such classes efficiently to be classified in STFT-ENGB for further operations.

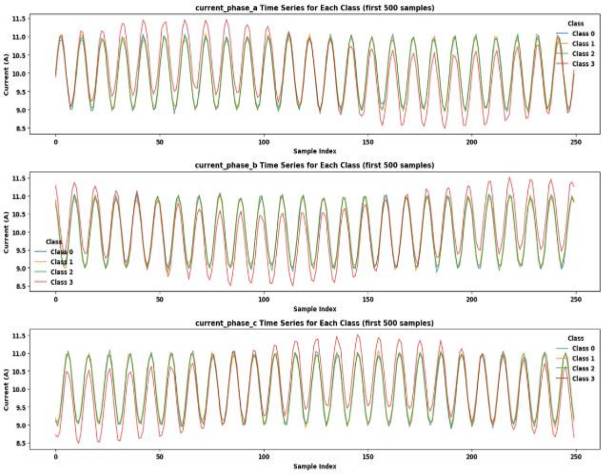

Figure 8: Current time series for each phase (A, B, C) and class in power signal processing using analysis TFA

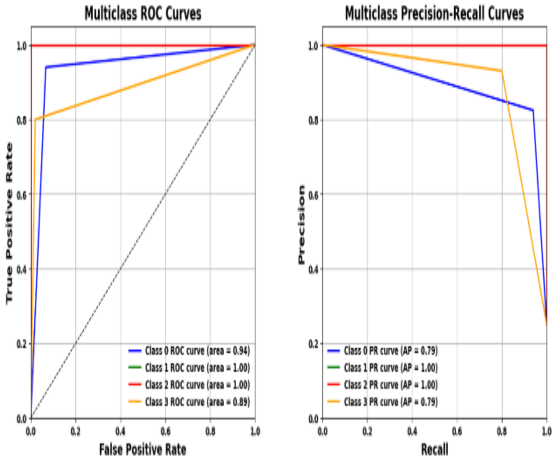

Figure 9: Multiclass ROC and precision-recall curves for power signal processing based on TFA

4.4 Multiclass ROC and precision-recall curves

Figure 9 shows both the multiclass ROC (receiver operating characteristic) curves and precision-recall curves for a power signal processing model from a TFA understanding. For the ROC curve, each class is plotted for the true positive rate (TPR) against the false positive rate (FPR). The ROC and PR curve discrepancies reveal the Classes 3 and 0 to perform, and the relative Classes 1 and 2 reveal intrinsic class level. In contrast, the classes 1 and 2 have perfect scores and represented in terms of features that were stronger and easily distinguishable. Class 3 and 0 predictions were negatively affected by noise or intra-class variability. In left side, it indicates the multiclass ROC curves and right side it represents the multiclass precision-recall curves. In multiclass ROC curves, the x-plane depicts the false positive rates and y- plane depicts the true positive rates. In multiclass precision-recall curves, the x- plane illustrates the recall score, which ranges from 0 to 1, and y-plane indicates the precision score, ranges from 0 to 1. These observations indicate that target data augmentation or class-by-class tuning.

4.5 Statistical test significance

The statically significance McNemar test yields a chi-squared statistic of 3.27 and a p-value of 0.0704, indicating an observed improvement that was not statistically significant at the 0.05 level. When the accuracy gain appears, it equates 7 correct classifications per 1,000 instances, which can be critical for timely and accurate detection of power quality disturbances in real-time smart grid environments.

The comparison of Training Time vs Inference Latency was illustrated, in Figure10. This plot shows a comparison between the training time and the inference latency of two models; SVM and STFT- ENGB. The fastest training achieved by SVM was 0.017s and the lowest latency of inference was 0.00044s, which suits light weight, real-time applications. STFT + ENGB took 1.223s to train, which is indicative of the more elaborate learning procedure and had low latency of 0.00123s. STFT-ENGB model was easy to train and hence the expensive training costs was less.

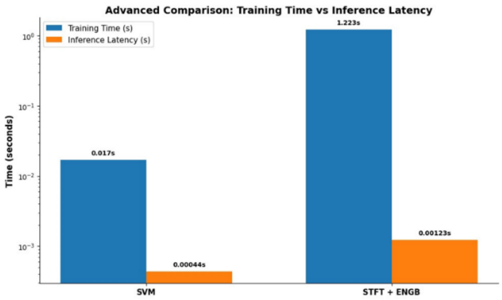

Figure 10: Training time vs inference latency

The scalability test enables to conclude the data point changes, and the training time increases with gradual changes; with 1.1 s size with 800--1000 samples increases gradually to 1.2 s, which proves its linear scalability. The inference latency is with 0.01 s size with 800-1000 samples increases gradually to 0.014 s, which proves its linear scalability, confirming the predictive potential of the model in real-time. These outcomes show that the STFT - ENGB model was effective and resistant to load. The scalability criteria and the real time feasibility used to accomplish power quality disturbances was illustrated in Figure11.

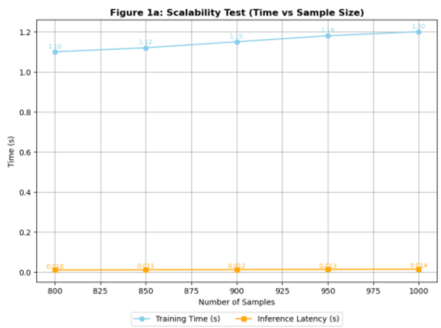

Figure 11: Output of scalability test

4.6 Metrics for evaluating the effectiveness of the proposed model

- **Accuracy:** Measures the overall rate of correct predictions. This indicator shows how successfully the system detects various categories of power quality problems within the smart grid setting

- **Precision:** It indicates how many actual positive cases exist within all the predicted positive outcomes. This metric helps the system to detect true PQD events correctly and the false alarms are kept at a low level.

- **Recall:** Measures the model's ability to detect all actual instances of a class. It attributes the strength exhibited by the model in response to different transient and fluctuation patterns of voltages.

- **F1-Score:** Balances precision and recall using their harmonic mean. The metric shows the balanced performance in real-time tradeoff between sensitivity and specificity.

The performance results of the proposed method are discussed in this section. The outcomes are contrasted with the other approaches, Support vector machine (SVM) [21], and Random Forest [22]. The Comparative performance of STFT-ENGB models, precision, F1-score, accuracy, and recall, was illustrated in Table 4 and Figure11.

Table 4: Comparative performance of STFT-ENGB models, precision, F1-score, accuracy, and recall.

Methods	**F1-Score (%)**	**Precision (%)**	**Accuracy (%)**	**Recall (%)**
SVM [21]	-	-	98.05	-
RF [22]	95.5	95.5	95.5	95.5
STFT-ENGB [Proposed]	**98.62**	**98.65**	**98.75**	**98.6**

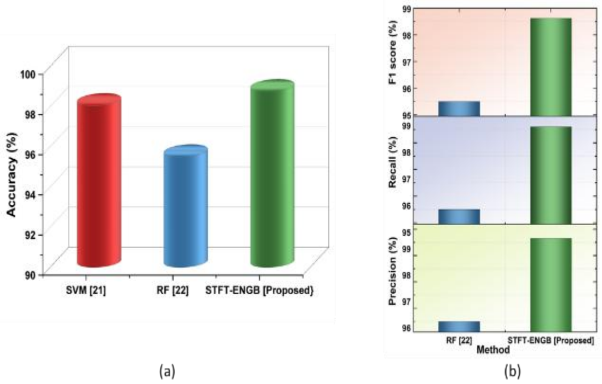

Figure 11: Evaluation of STFT-ENGB models, (a) accuracy and (b) recall, precision, and F1-score for enhancing power quality distribution detection.

The proposed STFT-ENGB approach is used for power quality monitoring through efficient time-frequency feature extraction and adaptive boosting classification. The system achieves an accuracy of 98.75%, showcasing its strong capability in correctly identifying power quality disturbances across various scenarios. With a precision of 98.65% and a recall of 98.6%, it reliably identifies disturbance patterns while minimizing false positives and missed events. Furthermore, the F1-score of 98.62% validates the model's robust and superior performance in a balanced way. These metrics validate that the STFT-ENGB approach has an effective solution for real-time smart grid disturbance detection.

5 Discussion

Power signal processing improves electrical grid and microgrid monitoring and control, particularly on the electrical grids due to more renewable energy. TFA methods might not sensitive enough to measure quickly, and the nonlinear nature of waveforms caused by power electronics-based renewable sources [15]. These techniques were frequently sensitive or flexible and it was desirable to observe faint or temporary perturbations in different loading conditions. The SVM model [21] based on power signal processing and feature extraction algorithm with TFA are its sensitivity to input data quality and levels of noise, which has performance metrics accuracy of (98.05%). The dependence of the model on pre-defined feature extraction methods can fail to completely reflect dynamic variations. RF models could involve heavy computations of building numerous decision trees, not suitable in real-time smart grid applications [22]. RF models have performance metrics accuracy of (95.05%), for modeling complex dimensional temporal dependencies in time-series PQD data. The RF algorithm can be affected by its performance when using imbalanced datasets in PQD settings. Furthermore, the effectiveness of the model highly relies on feature engineering and prevents the ability to adapt to unprecedented disturbances without retraining. Spectral leakage was commonly mitigated through windowing methods which minimize distortion in frequency analysis at the risk of sharp signal states. The cultured measures used to minimize leakage, used in real-time systems, might be heavier load on the delays. Feature robustness plays an essential role in excessive filtering to control leakage for accurate classification. The trade-off was extremely crucial in power signal analysis and smart grid applications.

To overcome these limitations, the suggested STFT-ENGB approach, incorporates adaptive noise reduction techniques for improved input data quality, providing better performance robustness. The algorithm employs real-time feature extraction using STFT to minimize computational burdens and capture dynamic changes effectively. The flexibility in STFT-ENGB makes it possible to fine-tune and verify it for a variety of power systems and operating regimes.

6 Conclusion

Power signal processing using the TFA method for evaluating non-stationary signals, which decomposes the signal into the transient system as well as frequency domains. TFA enables a composite representation of a signal's frequency spectrum over time, allowing it to efficiently record transient and time-dependent incidents. The dataset was collected from Kaggle. A normalization technique of z-score used for preprocessing the noise reduction. The power signals were subjected to discriminative, time-localized feature extraction using the STFT. To create a single representation, these extracted features were joined by using a late fusion technique. The STFT-ENGB model for enhancing the recognition of power quality disturbances with energy grid applications. Extensive experiments demonstrated that the proposed STFT-ENGB model outperforms baseline architectures, achieving superior results in terms of accuracy (98.75%), F1-score (98.62%), recall (98.6%), and precision (98.65%) to ensure the distribution of power qualities. These findings offer a promising solution for real-time power signal monitoring in smart grid environments, facilitating intelligent fault diagnosis and improving the overall resilience and responsiveness of modern electrical infrastructure. The TFA signal processing and feature extraction algorithm does not deliver the expected performance in the presence of noise and rapidly varying signals, or cannot be computationally feasible for systems with restricted resources. Future research can investigate the incorporation of sophisticated ML methods for the real-time processing of power signals, improving the efficiency and accuracy of feature extraction algorithms. The use of TFA-based algorithms in smart grid and

Internet of Things (IoT) applications has the potential to enhance energy management and fault detection.

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