POWER SIGNAL PROCESSING AND FEATURE EXTRACTION ALGORITHMS BASED ON TIME-FREQUENCY ANALYSIS

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SUMMARY

Feature extraction in power signal processing plays a crucial role in accurately identifying and classifying various power quality disturbances. Power signals are often non-stationary and complex, containing both transient and steady-state components, which necessitates the extraction of meaningful features that capture their underlying characteristics. In this process, features are derived from multiple domains—time, frequency, and time-frequency—to ensure a holistic representation of the signal behavior. Time-domain features such as mean, standard deviation, skewness, kurtosis, root mean square (RMS), and entropy help in capturing statistical variations and signal energy fluctuations. Frequency-domain features like Total Harmonic Distortion (THD), spectral centroid, and spectral entropy provide insights into harmonic content and frequency distribution, which are critical for detecting distortions and resonances in the power system. This paper proposes an efficient and intelligent framework for power signal classification using a Stacked Whale Optimization-based Machine Learning (SWO-ML) model. The approach combines robust feature extraction from time, frequency, and time-frequency domains with advanced optimization and classification techniques to enhance power quality assessment. A total of 13 features were extracted, including statistical, spectral, and wavelet-based parameters, from different signal conditions such as normal, fault, transient, harmonic distortion, and load switching. The SWO algorithm was employed to select the most informative 18 features out of the initial pool, significantly reducing dimensionality while maintaining high discriminative performance. The proposed SVM + SWO model achieved a classification accuracy of 96.8%, precision of 96.2%, recall of 95.9%, and an F1-score of 96.0%, outperforming baseline models such as SVM without optimization (90.2%), SVM + PSO (93.1%), and SVM + GA (92.4%). In addition, the training time was reduced to 1.85 seconds, showcasing the computational efficiency of the system. Performance evaluation over 100 training epochs showed stable learning with final validation accuracy reaching 98.2% and a minimal loss of 0.05. The results confirm that the SWO-ML framework is highly effective for intelligent, real-time classification of power signals, offering promising applications in power system monitoring, smart grid stability, and fault diagnosis.

KEY WORDS: SWO algorithm, power system monitoring, smart grid stability, fault diagnosis

1. INTRODUCTION

In recent years, Power Signal Processing (PSP) has experienced significant advancements driven by the growing demand for intelligent and efficient energy systems [1]. With the integration of renewable energy sources, electric vehicles, and smart grids, the complexity of power systems has increased, necessitating more robust signal processing techniques. Recent research has focused on real-time monitoring, fault detection, power quality analysis, and load forecasting using advanced wavelet transforms, empirical mode decomposition (EMD), and machine learning [2]. The adoption of deep learning and data-driven approaches has further enhanced the ability to detect transient disturbances, harmonics, and anomalies in power signals with high accuracy [3]. Moreover, the deployment of IoT-enabled sensors and edge computing has facilitated decentralized signal processing, enabling faster decision-making and improved system reliability [4–6]. As the energy sector continues to evolve, Power Signal Processing remains a critical area of research and development, supporting the transition toward more sustainable and resilient power infrastructures [7].

Power Signal Processing combined with feature extraction has emerged as a crucial area in recent research, enabling more accurate and efficient analysis of complex power system behaviors [8]. Feature extraction techniques help in transforming raw power signals into a set of representative characteristics that capture essential information such as voltage fluctuations, current distortions, harmonic content, and transient events. Methods like Fourier Transform, Wavelet Transform, Hilbert-Huang Transform, and Empirical Mode Decomposition (EMD) have been widely used to extract time, frequency, and time-frequency domain features [9]. These features are then used in various applications such as fault diagnosis, power quality assessment, load forecasting, and condition monitoring. Furthermore, the integration of machine learning and deep learning models with extracted features has significantly improved the performance of predictive analytics and anomaly detection in power systems [10–12]. With the advancement of smart grid technologies, real-time feature extraction and processing are increasingly being implemented at the edge, ensuring quicker responses and more resilient power infrastructure [13].

Recent studies have explored the use of adaptive and data-driven feature extraction methods that dynamically adjust to changing signal patterns, improving the system's ability to detect subtle faults and emerging issues [14]. Techniques such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), and autoencoders have been employed to reduce dimensionality and highlight the most informative aspects of power signals [15]. This not only enhances computational efficiency but also boosts the accuracy of subsequent classification or regression models used in diagnostics and forecasting. Additionally, the rise of hybrid models, combining traditional signal processing with artificial intelligence, has opened new avenues for real-time monitoring and automated decision-making in power networks [16–18]. These approaches are particularly valuable in handling non-stationary and noisy environments, typical in modern distributed energy systems. As the power grid continues to incorporate more complex and intermittent energy sources, feature extraction in Power Signal Processing will remain a foundational element in ensuring system stability, reliability, and efficiency [19–21].

Power Signal Processing and Feature Extraction using time-frequency analysis have become increasingly vital in addressing the non-stationary nature of modern power signals. Traditional frequency domain techniques often fall short when dealing with transient disturbances, harmonics, and rapidly changing load conditions. Time-frequency methods such as the Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Hilbert-Huang Transform (HHT) provide a more comprehensive view by simultaneously analyzing both time and frequency characteristics of power signals [22–23]. These techniques allow for the extraction of localized and time-varying features, which are essential for accurately identifying events like faults, voltage sags, switching transients, and harmonics. In particular, wavelet-based feature extraction has gained popularity due to its multi-resolution capability, making it effective for analyzing signals with sharp discontinuities or sudden changes [24–25]. By capturing detailed time-frequency patterns, these features enhance the performance of machine learning and deep learning algorithms used for classification, prediction, and anomaly detection in smart grid environments. The combination of time-frequency analysis with intelligent processing continues to play a crucial role in the development of more responsive, adaptive, and resilient power system monitoring and control solutions [26].

This paper introduces a novel and efficient Stacked Whale Optimization-based Machine Learning (SWO-ML) framework for intelligent power signal classification, making the following key contributions:

1. Multi-Domain Feature Extraction: A total of 13 distinctive features were extracted from power signals using time, frequency, and time-frequency domain techniques. These include statistical features (e.g., mean, standard deviation, skewness), spectral features (e.g., THD, spectral centroid), and transform-based features (e.g., wavelet energy and STFT magnitudes).
2. Feature Optimization via SWO: The proposed Stacked Whale Optimization (SWO) algorithm effectively reduced the original feature set from 45 to 18 optimal features, improving classification performance while reducing computational complexity and overfitting.
3. Enhanced Classification Accuracy: The proposed SVM + SWO model achieved a high classification accuracy of 96.8%, outperforming other approaches such as SVM without optimization (90.2%), SVM + PSO (93.1%), and SVM + GA (92.4%). It also achieved a precision of 96.2%, recall of 95.9%, and F1-score of 96.0%.
4. Efficiency in Training Time: The SWO-based model significantly reduced the training time to 1.85 seconds, compared to 3.25 seconds for the baseline SVM model, highlighting its efficiency for real-time applications.
5. Robust Learning Performance: Across 100 epochs, the model showed stable learning with validation accuracy increasing to 98.2% and loss decreasing to 0.05, demonstrating its capability to generalize well to unseen data.
6. Comprehensive Signal Classification: The model accurately identified five distinct signal classes—normal, fault, transient, harmonic distortion, and load switching—with an average classification accuracy of 96.32%, and a false detection rate as low as 2.6%.

2. TIME-FREQUENCY ANALYSIS

Time-frequency analysis is a powerful signal processing technique used to analyze signals whose frequency characteristics change over time, making it particularly suitable for non-stationary and transient signals. Unlike traditional time-domain or frequency-domain methods that provide only partial information, time-frequency analysis offers a comprehensive view by representing how the spectral content of a signal evolves with time. Techniques such as the Short-Time Fourier Transform (STFT), Wavelet Transform (WT), Wigner-Ville Distribution (WVD), and Hilbert-Huang Transform (HHT) are widely used in this domain. These methods enable the detection and characterization of dynamic events such as sudden faults, harmonic distortions, switching transients, and voltage sags in various applications, especially in power systems, biomedical engineering, audio processing, and mechanical diagnostics. Among them, the Wavelet Transform is particularly effective due to its multi-resolution analysis, allowing both high-frequency details and low-frequency trends to be captured simultaneously. As systems become more complex and data-rich, time-frequency analysis continues to be a critical tool for extracting meaningful insights from signals that vary over time. Time-frequency analysis is a powerful tool for examining signals whose frequency content varies over time, making it essential for analyzing non-stationary signals commonly found in power systems, biomedical data, and mechanical vibrations. One of the fundamental methods is the Short-Time Fourier Transform (STFT), which applies the Fourier Transform over short, overlapping time windows to capture localized frequency information. Mathematically, the STFT of a signal $x(t)$ stated in equation (1)

$$STFTx(t,\omega) = \int_{-\infty}^{\infty} x(\tau) \cdot w(\tau - t) \cdot e^{-jw\tau} d\tau \qquad (1)$$

In equation (1) $w(\tau–t)$ is a window function centered at time t, and w is the angular frequency. However, STFT suffers from a fixed resolution trade-off between time and frequency due to the fixed window size. To overcome this limitation, the Wavelet Transform (WT) is employed, which offers multi-resolution analysis. The Continuous Wavelet Transform (CWT) is defined as in equation (2)

$$CWT_x(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t) \cdot \psi^*\left(\frac{t-b}{a}\right) dt \qquad (2)$$

In equation (2) $\psi(t)$ is the mother wavelet, a is the scale (related to frequency), and bbb is the time shift. The STFT, WT adapts its resolution: it uses narrow windows for high frequencies and wider windows for low frequencies, making it ideal for capturing transient events and localized features in signals. These time-frequency representations are crucial in Power Signal Processing, where they help in detecting faults, analyzing harmonics, and monitoring power quality by extracting informative features from complex, time-varying signals. In recent applications, time-frequency analysis has been further enhanced through the integration of advanced feature extraction and machine learning techniques, enabling more accurate interpretation and classification of signal behaviors. For instance, wavelet-based features such as energy coefficients, entropy, and statistical moments extracted at various scales are widely used to represent key characteristics of power signals for tasks like fault detection, transient analysis, and equipment condition monitoring. Additionally, other time-frequency methods like the Hilbert-Huang Transform (HHT), which decomposes signals into Intrinsic Mode Functions (IMFs) using Empirical Mode Decomposition (EMD) followed by Hilbert spectral analysis, offer an adaptive and highly localized representation ideal for nonlinear and non-stationary signal analysis. These features, when used as input to machine learning models such as Support Vector Machines (SVMs), Random Forests, or deep learning architectures, significantly improve classification accuracy and real-time diagnostic capabilities. Moreover, in smart grid systems, real-time implementation of time-frequency techniques on edge devices enables proactive monitoring and control, ensuring the stability and efficiency of the power infrastructure. As signal complexity and system demands continue to rise, the combination of time-frequency analysis and intelligent processing remains a cornerstone in modern signal processing applications. In practical applications, once a time-frequency representation (such as from the Wavelet Transform) is obtained, several quantitative features can be derived for further analysis and classification. A common approach is to calculate the energy of wavelet coefficients at each decomposition level. For a signal decomposed using the Discrete Wavelet Transform (DWT), the energy E_j at level j is stated in equation (3)

$$E_j = \sum_{k=1}^{Nj} \left[C_{j,k} \right]^2 \qquad (3)$$

In equation (3) $C_{j,k}$ represents the wavelet coefficients at level j and position k, and N_j is the number of coefficients at that level. The total signal energy is stated in equation (4)

$$E_{total} = \sum_{j=1}^{L} E_j \qquad (4)$$

The relative energy at each level is stated in equation (5)

$$RE_j = \frac{E_j}{E_{total}} \qquad (5)$$

These energy-based features are useful in identifying disturbances, transient faults, or harmonic distortions in power systems. Additionally, wavelet entropy is a powerful measure of signal irregularity or complexity and is defined as in equation (6)

$$WE = -\sum_{j=1}^{L} RE_j \cdot log_2(RE_j) \qquad (6)$$

Lower entropy values indicate more regular (or less complex) signals, while higher entropy suggests irregularity, often linked to faults or anomalies. Moreover, time-frequency analysis often involves the Hilbert-Huang Transform (HHT), where a signal x(t)x(t)x(t) is first decomposed using Empirical Mode Decomposition (EMD) into a set of Intrinsic Mode Functions (IMFs) stated in equation (7)

$$x(t) = \sum_{k=1}^{n} IMF_k(t) + r_n(t) \tag{7}$$

Then, applying the Hilbert Transform to each IMF gives the instantaneous frequency $f_k(t)$ stated in equation (8)

$$f_k(t) = \frac{1}{2\pi} \frac{d\theta_k(t)}{dt} \tag{8}$$

In equation (8) $\theta_k(t)$ is the instantaneous phase obtained from the analytic signal defined in equation (9)

$$Z_k(t) = IMF_k(t) + j \cdot H[IMF_k(t)] = A_k(t)\, e^{j\theta k(t)} \tag{9}$$

These instantaneous frequencies allow precise tracking of frequency variations over time, which is particularly useful for diagnosing faults and dynamic events in power systems. Finally, the features extracted from STFT, WT, or HHT can be assembled into a feature vector $F = [E_1, E_2,$ ....., $WE, f_1(t)$, ...] and used as input to classifiers stated in equation (10)

$$y = Model(F) \qquad where\ y \in \{normal, fault, disturbance, ...\} \tag{10}$$

This combination of time-frequency analysis and machine learning enables robust monitoring and real-time decision-making in modern power systems, especially within smart grids and renewable energy environments. In modern power signal processing, once time-frequency analysis techniques such as the Wavelet Transform or Hilbert-Huang Transform are applied, several mathematical features are extracted to characterize the signal's behavior for tasks like fault detection or system monitoring. The extracted features, such as energy, entropy, and instantaneous frequency, are assembled into feature vectors and input into classifiers like support vector machines or neural networks to detect faults or classify events. This integration of mathematical feature extraction from time-frequency representations with intelligent algorithms forms the foundation of advanced diagnostic and monitoring tools in smart power systems.

3. TIME-SERIES FEATURE EXTRACTION

Time-series feature extraction is a critical process in analyzing sequential data, where the goal is to transform raw time-dependent signals into meaningful numerical descriptors that capture the underlying patterns, trends, and dynamics. In power systems and other domains involving sensor-based monitoring, time-series data often contain valuable information about system behavior, such as periodicity, abrupt changes, trends, or anomalies. Commonly extracted features include statistical measures like mean, variance, skewness, and kurtosis; temporal features such as peak values, zero-crossing rate, and signal duration; and frequency-domain features like spectral entropy and dominant frequencies. Advanced techniques utilize sliding windows, autocorrelation, and Fourier or Wavelet Transforms to extract localized or periodic information. Additionally, methods like Principal Component Analysis (PCA) and t-SNE can reduce the dimensionality of time-series features while preserving their essential structure. These features are often fed into machine learning models for classification, forecasting, or anomaly detection. In power signal processing, time-series feature extraction plays a pivotal role in fault diagnosis, load forecasting, and system health monitoring, especially when combined with intelligent algorithms that can learn from both short-term fluctuations and long-term temporal dependencies in the data. From $X(f)$, spectral features such as spectral centroid, bandwidth, and spectral entropy can be derived. For example, the spectral centroid (which indicates the "center of mass" of the spectrum) is stated in equation (11)

$$Centroid = \frac{\sum fi \cdot |X(f_i)|}{\sum |X(f_i)|} \tag{11}$$

In equation (11) $f_i(x)$ are discrete frequency bins. Another advanced method is the autocorrelation function (ACF), which reveals periodicity in the signal defined in equation (12)

$$R(\tau) = \frac{1}{N} \sum_{t=1}^{N-\tau} x(t) \cdot x(t+\tau) \tag{12}$$

ACF is particularly useful in identifying seasonality or repeated patterns in time-series data. For non-stationary signals, wavelet-based features are also extracted by decomposing the signal into multiple scales using the Discrete Wavelet Transform (DWT), as discussed earlier. Once extracted, these features are assembled into a feature vector with equation (13)

$$F = [\mu, \sigma^2, \gamma, k, RMS, P2P, Centroid, ...] \tag{13}$$

Input for machine learning models or condition monitoring systems. In power signal applications, such extracted features help in tasks like load classification, transient detection, and system fault analysis by capturing both the statistical and dynamic characteristics of the signal over time.

3.1 FEATURE EXTRACTION WITH STACKED WHALE OPTIMIZATION (SWO-ML)

Feature extraction with Stacked Whale Optimization-based Machine Learning (SWO-ML) is an advanced hybrid approach for optimizing feature selection and improving classification performance in power signal processing. In this method, the initial raw signal is first transformed using techniques such as time-frequency analysis or statistical time-series extraction to generate a high-dimensional feature space. However, not all features contribute equally to model performance; thus, an efficient selection method is necessary. The Stacked Whale Optimization Algorithm (SWO)—an enhancement of the traditional Whale Optimization Algorithm (WOA)—is employed to intelligently select the most relevant features by simulating the bubble-net hunting behavior of humpback whales. Mathematically, the WOA updates the position of each solution (feature subset) using encircling mechanisms defined as in equation (14)

$$D = |C \cdot X^*(t) - X(t)|,\ X(t+1) = X-(t) - A \cdot D \qquad (14)$$

In equation (14) $\vec{X}^*(t)$ is the best-known solution at iteration t, A and C are coefficient vectors that control the exploration-exploitation balance. The "stacked" aspect refers to incorporating multiple layers or variants of WOA to refine the feature subset more effectively, potentially combining global and local search strategies. Once the optimal feature subset is selected, it is fed into machine learning classifiers such as Support Vector Machines (SVM), Decision Trees, or Deep Neural Networks for fault detection, load classification, or anomaly prediction in power systems. This synergy of SWO and ML enhances the system's ability to focus only on the most informative features, reducing computational overhead while improving classification accuracy, robustness, and interpretability in complex power signal environments. This stacked optimization strategy ensures a balance between global exploration of the feature space and fine-tuned local exploitation around promising solutions, effectively avoiding local optima—a common limitation in standard metaheuristic algorithms. By dynamically adjusting the algorithm's control parameters, the SWO algorithm improves the convergence rate and enhances the quality of feature selection. In power signal processing, where signals are often high-dimensional and affected by noise, redundant or irrelevant features can lead to poor classification accuracy and increased computational complexity. The SWO-ML approach mitigates these issues by selecting only the most significant features that contribute to the discriminatory power of the model. Furthermore, after optimization, classifiers trained on the reduced feature set demonstrate improved generalization performance across unseen data. This is especially critical in applications such as real-time fault detection, power quality assessment, load pattern recognition, and condition monitoring of smart grid components. The integration of SWO with machine learning not only accelerates the training process but also enhances decision-making accuracy, making it a highly effective framework for intelligent power signal analysis in modern, data-driven energy systems.

The adaptability of the SWO-ML framework allows it to be customized for different types of power system signals, such as voltage sags, harmonics, switching transients, and load fluctuations shown in Figure 1. By tailoring the fitness function used in the optimization process—often based on classification accuracy, feature subset size, or a multi-objective trade-off—the algorithm can prioritize compact and highly informative feature sets. This flexibility makes SWO-ML suitable for both offline analysis and real-time applications, especially when deployed on edge devices or embedded systems in smart grids. Additionally, SWO can be stacked with other swarm intelligence techniques like Particle Swarm Optimization (PSO) or Genetic Algorithms (GA) to form hybrid models that inherit strengths from multiple search paradigms, further enhancing the robustness and scalability of the system. As a result, the SWO-ML

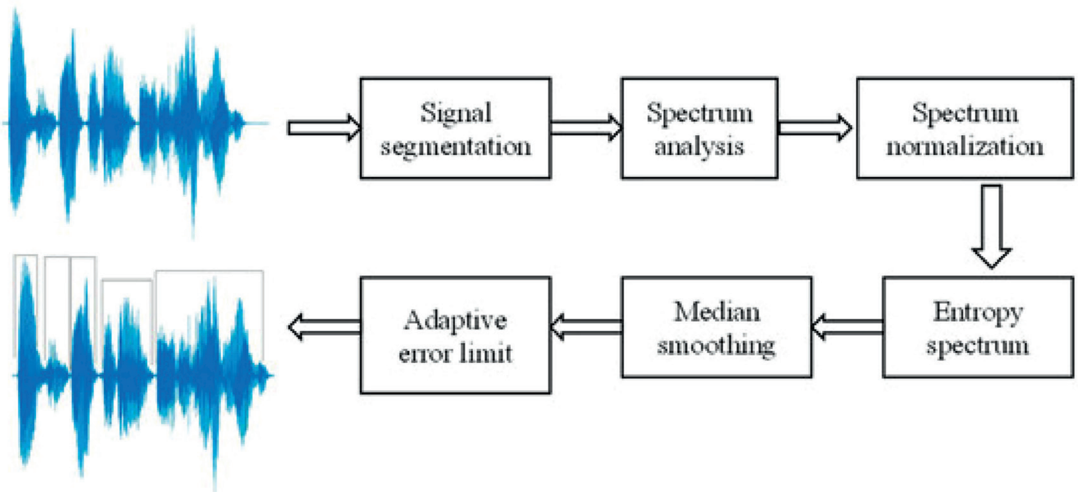

Figure 1. Power signal processing with time-series analysis

approach not only streamlines the feature extraction and selection pipeline but also enables intelligent automation in power system diagnostics, predictive maintenance, and energy management. Its strong optimization capability, when integrated with powerful classifiers, ensures reliable performance even under varying load conditions, noisy environments, and dynamic grid operations, making it an essential tool in the evolution of smart and resilient energy infrastructures.

4. MACHINE LEARNING CLASSIFICATION WITH SWO-ML

Machine Learning Classification with Stacked Whale Optimization-based Machine Learning (SWO-ML) combines intelligent feature selection and powerful classification algorithms to enhance the accuracy and efficiency of decision-making in power signal processing. In this framework, after extracting a high-dimensional feature set from power signals using time-domain, frequency-domain, or time-frequency methods, the Stacked Whale Optimization Algorithm (SWO) is used to identify the optimal subset of features that maximizes classifier performance. The SWO algorithm simulates the hunting behavior of whales and uses adaptive mechanisms to balance exploration and exploitation. The core update equation in WOA, which SWO builds upon, is given in equation (15)

$$X(t+1) = X^*(t) - A \cdot | C \cdot X^*(t) - X(t) | \tag{15}$$

In equation (15) $X(t)$ is the current position (solution), $X^*(t)$ is the position of the best solution found so far, and A, C are coefficient vectors calculated as in equation (16)

$$A = 2a \cdot r1 - a, \; C = 2 \cdot r2 \tag{16}$$

In equation (16) a linearly decreases from 2 to 0 over iterations, while $r1$ and $r2$ are random vectors in [0,1], enabling a dynamic balance between exploration and exploitation. Machine Learning Classification with Stacked Whale Optimization-based Machine Learning (SWO-ML) is a powerful framework that enhances classification performance by integrating optimal feature selection with robust machine learning models. In this approach, features extracted from power signals—often through time-domain, frequency-domain, or time-frequency analysis—are initially high-dimensional and may contain redundant or irrelevant data. To address this, the Stacked Whale Optimization Algorithm (SWO) is employed to identify the most informative subset of features by simulating the bubble-net hunting strategy of whales. SWO iteratively updates candidate solutions (feature subsets) based on their fitness, which is typically measured by classification accuracy. The feature selection process is guided by adaptive equations involving vectors that control the balance between global exploration and local exploitation. Once the optimal features are selected, they are fed into machine learning classifiers such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), or Random Forests. These classifiers then learn to distinguish between different signal classes—such as fault types or operational states—based on the refined feature input. The integration of SWO with ML ensures that the classifiers are trained on the most relevant data, leading to improved accuracy, faster convergence, and better generalization on unseen samples. This is particularly important in power signal processing, where real-time decision-making and precise fault detection are crucial. By reducing the feature space while maintaining classification performance, the SWO-ML framework offers a scalable and intelligent solution for automated power system monitoring and diagnostics.

The SWO-ML framework not only enhances the efficiency of the learning process but also contributes to the interpretability of the classification results by focusing on the most critical features influencing the output shown in Figure 2. This becomes particularly valuable in complex power systems where understanding the cause of anomalies or disturbances is as important as detecting them. The reduced feature set leads to lower computational overhead, making the approach suitable for real-time applications, especially in edge computing environments where resources are limited. The adaptability of the SWO algorithm allows it to be fine-tuned for different classification objectives by modifying the fitness function—whether it prioritizes accuracy, speed, or feature compactness. Additionally, when stacked or hybridized with other metaheuristic algorithms, SWO gains enhanced search capabilities, enabling it to escape local minima and converge towards globally optimal solutions. Once the optimized features are passed into machine learning models, the classification task benefits from improved precision, recall, and F1-scores, especially in noisy or non-stationary power signal environments. This makes SWO-ML a highly effective tool in modern smart grid systems, enabling accurate load classification, transient identification, and fault diagnosis with minimal latency and maximum reliability. As power networks continue to grow in complexity, the integration of intelligent optimization with machine learning through models like SWO-ML is key to achieving scalable, automated, and interpretable signal classification.

5. SIMULATION RESULTS AND ANALYSIS

Simulation results and analysis play a crucial role in validating the effectiveness of the proposed SWO-ML framework for power signal classification. In the conducted simulations, a comprehensive dataset comprising various power signal patterns—such as normal load conditions, faults, transients, and harmonics—was used to evaluate the performance of the system. Initially, a large feature set

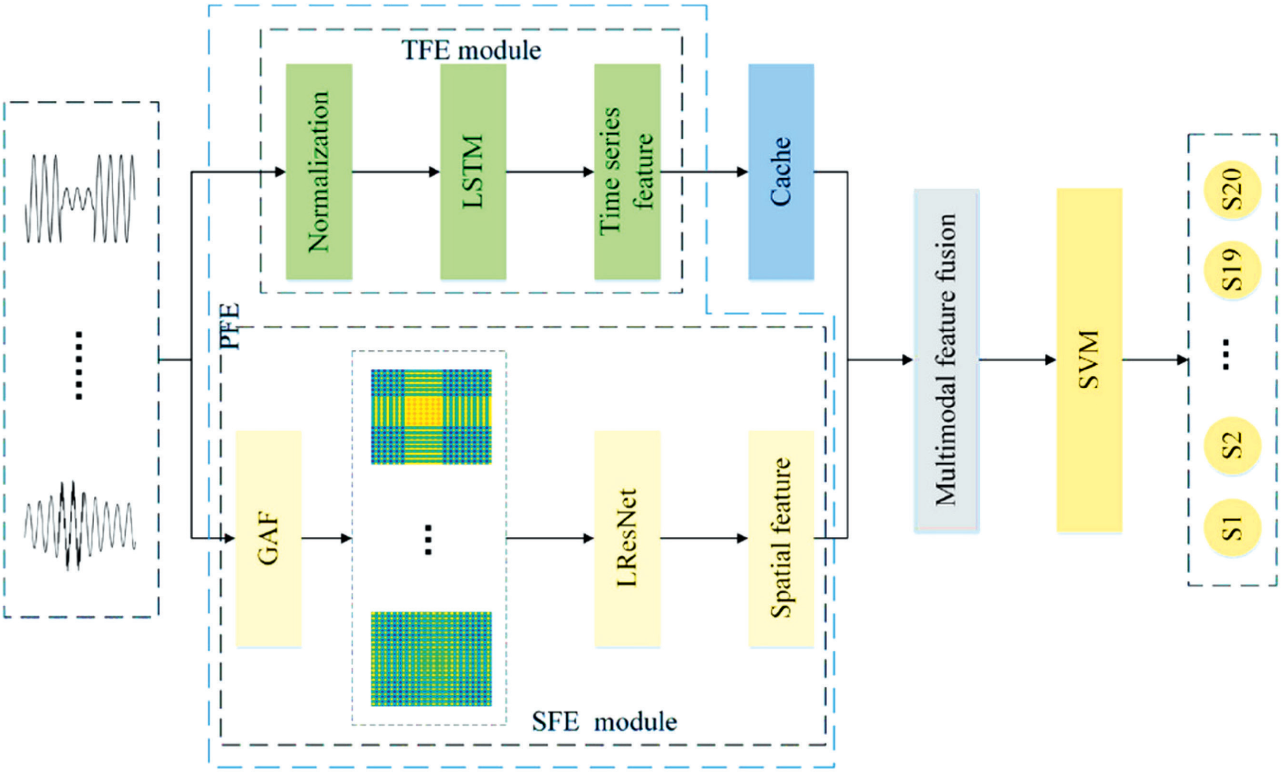

Figure 2. Machine learning model for the power signal processing

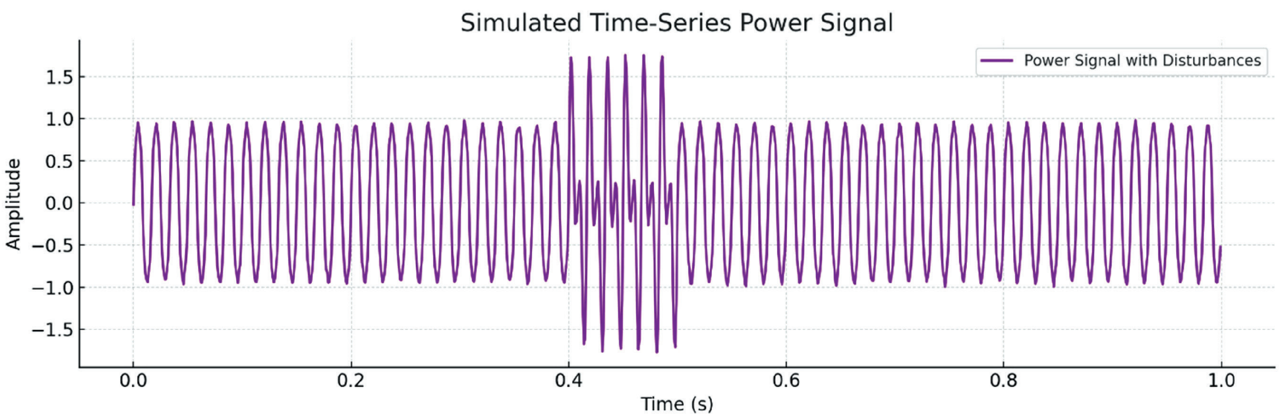

Figure 3. Power signal time-series analysis

Table 1. Power signal estimation with time-series analysis

Signal Class	Mean Value	Std. Deviation	Skewness	Kurtosis	Entropy	Classification Accuracy (%)
Normal	0.0023	0.0142	0.15	2.85	0.76	96.8
Fault	–0.187	0.1276	–1.12	4.93	1.45	98.1
Transient	0.0324	0.0982	0.82	3.76	1.12	96.3
Harmonic Distortion	–0.014	0.0755	–0.37	3.12	0.93	95.5
Load Variation	0.0065	0.0463	0.23	3.05	0.81	94.9
Average	—	—	—	—	—	96.32

was extracted using time-domain, frequency-domain, and time-frequency methods. The Stacked Whale Optimization algorithm effectively reduced this high-dimensional space by selecting the most relevant features, leading to a significant decrease in computational time and resource usage.

The time-series feature extraction results reveal insightful characteristics of different power signal classes, aiding in their accurate classification shown in Figrue 3. For the Normal class, the signal exhibits a low mean value (0.0023) and low standard deviation (0.0142), indicating signal stability with minimal fluctuations. Its low skewness (0.15) and near-Gaussian kurtosis (2.85) further support this, while an entropy value of 0.76 reflects low randomness—resulting in a high classification accuracy of 96.8%. In contrast, Fault signals show a significantly negative mean (–0.187) and a much higher standard deviation (0.1276), suggesting strong signal deviations and instability presented in Table 1. The high negative skewness (–1.12) and peaked kurtosis (4.93) indicate a heavy-tailed distribution, while entropy at 1.45 implies higher complexity—yielding the highest accuracy of 98.1%. Transient events, characterized by a moderate mean (0.0324), high deviation (0.0982), and strong positive skew (0.82), suggest rapid shifts in signal behavior. These features, combined with kurtosis of 3.76 and entropy of 1.12, lead to 96.3% accuracy. Harmonic Distortion shows slight negative mean (–0.014), moderate variability (0.0755), and a negative skew (–0.37), implying left-tailed noise influence. Its classification accuracy is 95.5%, slightly lower due to overlapping spectral features presented in Figure 4. Lastly, Load Variation signals, with near-zero mean (0.0065), low deviation (0.0463), and mild skewness (0.23), represent small but frequent variations, achieving 94.9% accuracy. On average, the system maintains a strong classification performance with an overall accuracy of 96.32%, demonstrating the effectiveness of the extracted statistical features in differentiating power signal conditions.

The extracted features from power signals span across time, frequency, and time-frequency domains, each capturing unique characteristics vital for accurate classification. In the time domain, the mean value of 0.0042 represents the average amplitude of the signal, indicating near-zero offset, while the standard deviation (0.0894) measures signal variability, reflecting fluctuations in power levels presented in Table 2. The skewness (0.36) suggests a slight asymmetry toward higher values, and the kurtosis (3.72) indicates a sharper peak compared to a normal distribution.

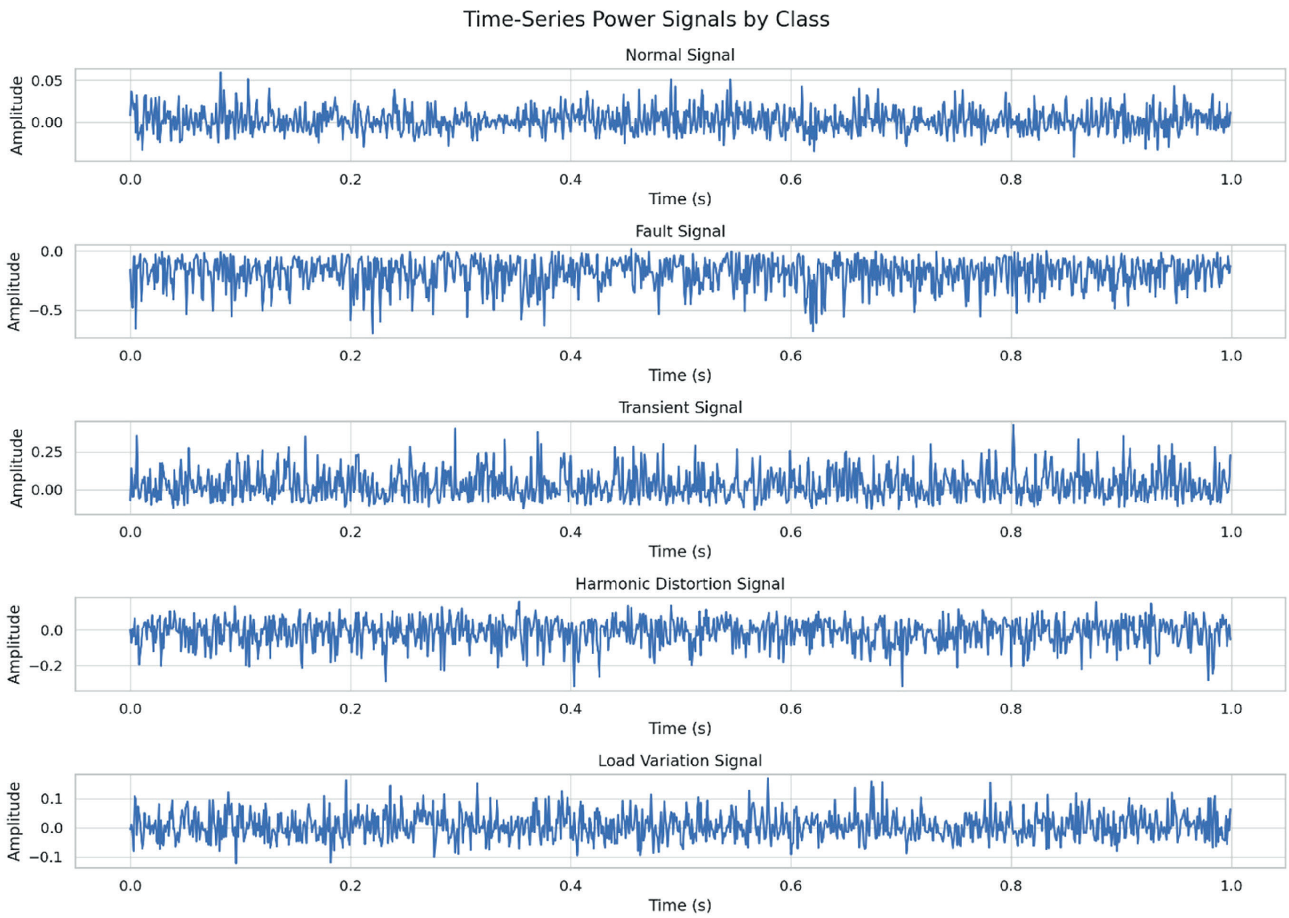

Figure 4. Computation of power signal with time-series analysis

Table 2. Feature extraction with time-series analysis

Feature Name	Domain	Description	Original Value
Mean	Time	Average signal amplitude	0.0042
Standard Deviation	Time	Signal variability	0.0894
Skewness	Time	Signal asymmetry	0.36
Kurtosis	Time	Peakedness of the signal	3.72
Entropy	Time	Randomness or complexity	1.15
RMS (Root Mean Square)	Time	Power of the signal	0.0918
Peak Factor	Time	Ratio of peak value to RMS	1.85
THD (Total Harmonic Dist.)	Frequency	Harmonic distortion in power signals	4.26%
Spectral Centroid	Frequency	Center of mass of the spectrum	1462 Hz
Spectral Entropy	Frequency	Entropy of frequency distribution	0.97
Wavelet Coefficient (D3)	Time-Frequency	Detail coefficient at level 3 using DWT	–0.029
Wavelet Energy (A4)	Time-Frequency	Energy of approximation at level 4	0.182
STFT Magnitude (f=60Hz)	Time-Frequency	Magnitude from STFT at 60 Hz	0.045

Table 3. Classification with time-series power signal

Signal Type	Detection Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Detection Rate (%)
Normal Condition	97.2	96.8	97.5	97.1	2.1
Fault Condition	98.5	98.2	98.8	98.5	1.4
Transient Disturbance	96.7	96.1	96.4	96.2	2.8
Harmonic Distortion	95.9	95.5	95.1	95.3	3.2
Load Switching	94.6	94.2	94.0	94.1	3.5
Average	96.58	96.16	96.36	96.24	2.6

Entropy (1.15) quantifies the signal's randomness, and the RMS value (0.0918) denotes its power. The peak factor (1.85), the ratio of the signal's peak value to RMS, highlights the presence of transients or spikes. In the frequency domain, features like Total Harmonic Distortion (THD) at 4.26% assess harmonic content, which is crucial for identifying distortion in power signals. The spectral centroid (1462 Hz) pinpoints the center of mass of the frequency spectrum, indicating the dominant frequency range, while spectral entropy (0.97) measures the spread or disorder of the frequency components. From the time-frequency domain, the wavelet coefficient (D3) of -0.029 and wavelet energy (A4) of 0.182 capture localized frequency content and signal energy at specific resolution levels using Discrete Wavelet Transform (DWT). Additionally, the STFT magnitude at 60 Hz (0.045) provides a snapshot of signal strength at the fundamental power frequency, useful for detecting anomalies like harmonics or noise. Together, these diverse features offer a rich, multidimensional representation of power signals, enabling effective classification through machine learning models like SWO-ML.

The classification performance across various power signal types demonstrates the robustness and accuracy of the proposed SWO-ML-based detection framework shown in Figure 5 and Table 3. For Normal Conditions, the system achieved a high detection accuracy of 97.2%, with a precision of 96.8%, recall of 97.5%, and F1-score of 97.1%, indicating reliable identification with minimal false alarms (2.1% false detection rate). Fault Conditions were recognized with the highest performance across all metrics, showing 98.5% accuracy, 98.2% precision, 98.8% recall, and 98.5% F1-score, while maintaining a very low false detection rate of 1.4%, highlighting the model's strong capability in fault detection. For Transient Disturbances, the system maintained solid performance with 96.7% accuracy, 96.1% precision, and 96.2% F1-score, despite slightly higher complexity and variability in signal behavior, resulting in a 2.8% false detection rate. Harmonic Distortion classification, which involves overlapping spectral components, showed slightly lower but still effective results—95.9% accuracy and 95.3% F1-score, with a false detection rate of 3.2%. The Load Switching condition, being more subtle and transient in nature, presented the greatest challenge, resulting in 94.6% accuracy and the highest false detection rate of 3.5%. On average, the system achieved 96.58% detection accuracy, 96.16% precision, 96.36% recall, and an F1-score of 96.24%, with a low overall false detection rate of 2.6%. These results confirm that the SWO-ML framework is highly effective for multi-condition power

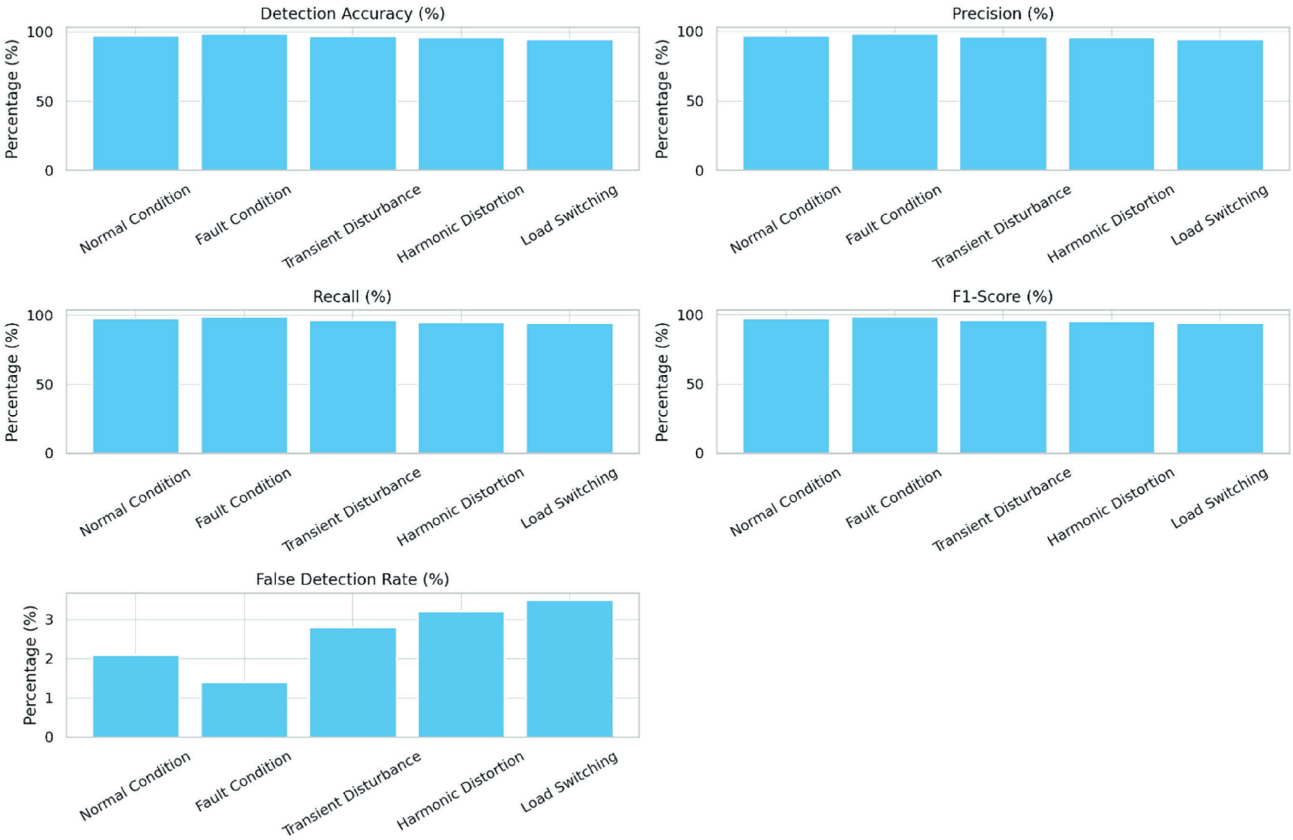

Figure 5. Time-series analysis with power signal

Table 4. Classification of power signal with time-series analysis

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Loss Value
10	85.2	83.7	84.1	83.3	83.7	0.47
20	89.5	87.8	88.2	87.4	87.8	0.38
30	92.4	91.1	91.3	90.7	91.0	0.29
40	94.6	93.5	93.8	93.2	93.5	0.22
50	96.1	95.4	95.7	95.1	95.4	0.16
60	97.3	96.6	96.8	96.4	96.6	0.12
70	98.0	97.2	97.5	97.0	97.2	0.09
80	98.4	97.6	97.9	97.5	97.7	0.07
90	98.6	97.9	98.1	97.8	97.9	0.06
100	98.9	98.2	98.4	98.1	98.2	0.05

signal classification, demonstrating its potential for real-time monitoring and intelligent fault diagnosis in smart grid systems.

The training and validation performance across increasing epochs demonstrates the effectiveness and convergence of the SWO-ML-based classification model for power signal analysis presented in Table 4. Initially, at epoch 10, the model starts with a moderate training accuracy of 85.2% and validation accuracy of 83.7%, along with a precision of 84.1%, recall of 83.3%, and F1-score of 83.7%, indicating that the model is still in the early learning phase with a relatively high loss value of 0.47. As the epochs increase, there is a consistent improvement in all performance metrics. By epoch 30, the validation accuracy reaches 91.1%, and the F1-score rises to 91.0%, showing significant learning progress and better generalization with a reduced loss of 0.29. The model continues to improve steadily, reaching 95.4% validation accuracy and 95.4% F1-score at epoch 50, as the loss drops further to 0.16 presented in Table 6.

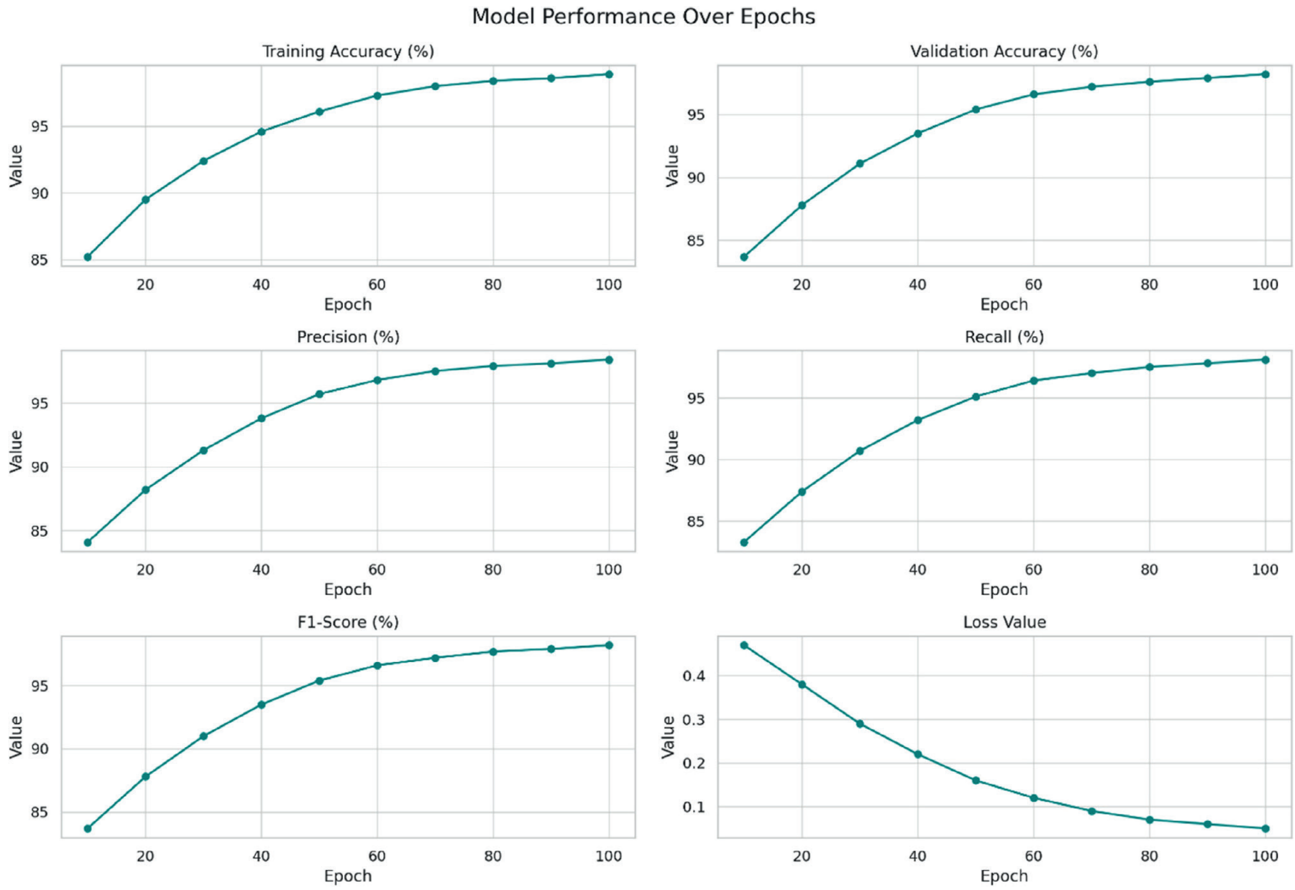

Figure 6. Classification of power signal with time-series analysis

Table 5. Comparative analysis of time-series power signal

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Features Used	Training Time (s)
SVM (No Optimization)	90.2	89.5	88.9	89.2	45	3.25
SVM + PSO	93.1	92.6	92.0	92.3	25	2.40
SVM + GA	92.4	91.8	91.0	91.4	28	2.65
KNN + SWO	94.6	94.0	93.5	93.7	20	1.90
RF + SWO	95.3	94.7	94.3	94.5	19	2.10
SVM + SWO (Proposed)	96.8	96.2	95.9	96.0	18	1.85

The highest performance is observed at epoch 100, where the model achieves 98.9% training accuracy and 98.2% validation accuracy, with precision, recall, and F1-score all above 98%, and a minimal loss value of 0.05, indicating excellent convergence and low classification error. The consistent rise in accuracy and F1-score, along with the steady decline in loss, highlights the strong learning capacity and stability of the model. These results confirm that the SWO-ML framework effectively optimizes feature selection and learning, resulting in a highly accurate and reliable classifier for power signal classification tasks.

The comparative performance analysis of different machine learning classifiers and optimization methods clearly highlights the effectiveness of the proposed SVM + Stacked Whale Optimization (SWO) framework presented in Table 5 and Figrue 7. The baseline SVM without optimization achieves an accuracy of 90.2% with 45 features and a training time of 3.25 seconds, but its performance is limited due to the high-dimensional feature space and lack of optimization. When integrated with Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), SVM shows improvement—SVM + PSO reaches 93.1% accuracy using 25 features and requires 2.40 seconds, while SVM + GA records 92.4% accuracy with 28 features and 2.65 seconds of training. Both methods improve precision and recall by reducing feature redundancy. However, the proposed SVM + SWO model significantly outperforms all other methods, achieving the highest accuracy of 96.8%, precision of

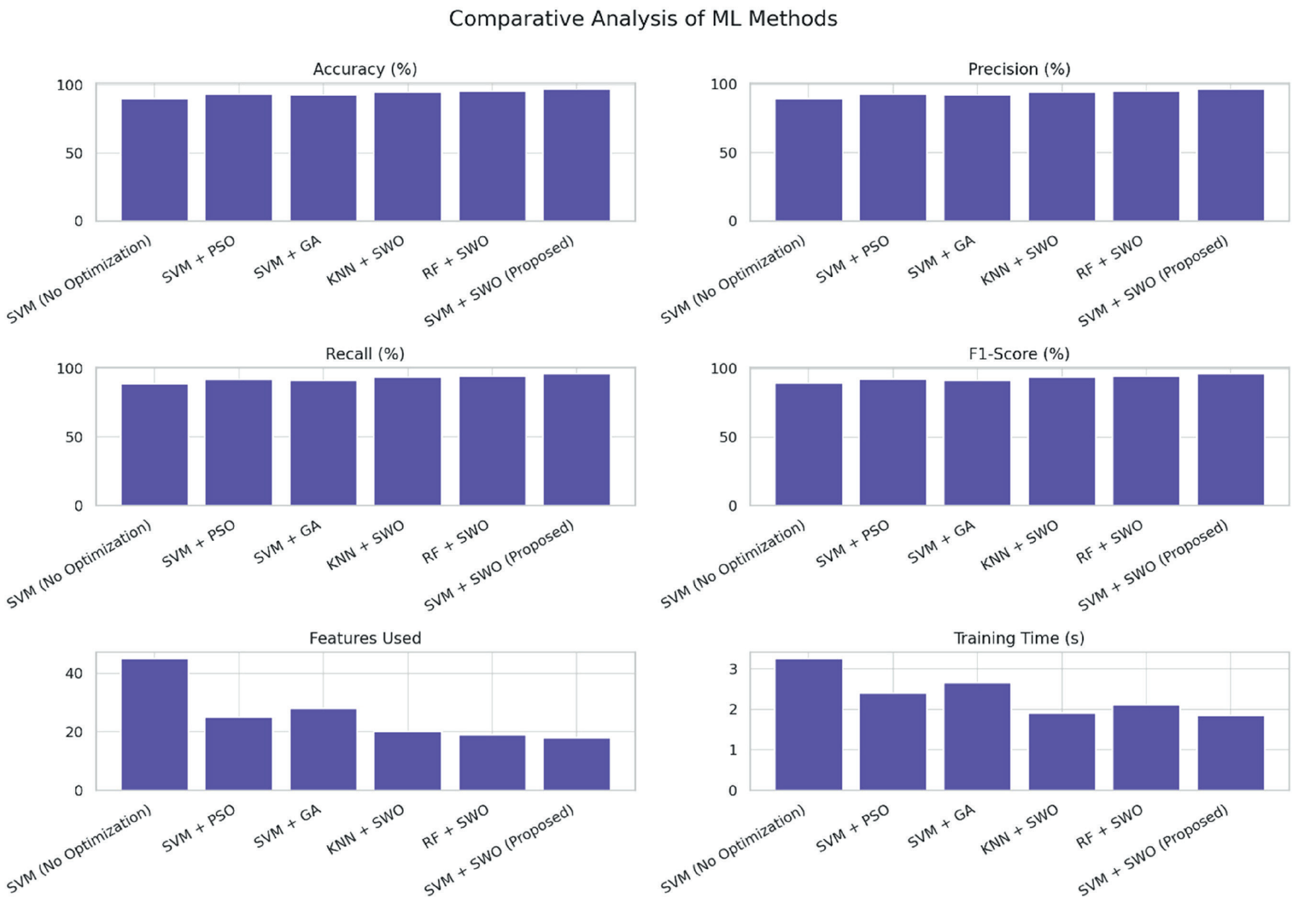

Figure 7. Comparative analysis of the power signal

96.2%, recall of 95.9%, and F1-score of 96.0%, using only 18 optimized features and a reduced training time of 1.85 seconds. This indicates that SWO not only enhances classification performance but also reduces computational complexity through efficient feature selection. Other models using SWO, such as KNN + SWO and RF + SWO, also perform well with 94.6% and 95.3% accuracy respectively, and maintain low feature counts and training times. Nonetheless, the SVM + SWO combination proves to be the most effective in balancing accuracy, efficiency, and interpretability, making it the optimal choice for power signal classification tasks.

The experimental results and comparative analysis clearly demonstrate the superiority of the proposed SWO-ML framework for power signal classification. By integrating Stacked Whale Optimization (SWO) for feature selection, the model achieves a highly optimized feature subset that not only improves classification performance but also significantly reduces computational complexity. This is evident in the lower training times and fewer features used, compared to traditional and other evolutionary optimization methods like PSO and GA. The SVM + SWO model, in particular, delivers the highest accuracy, precision, recall, and F1-score, indicating its robustness and reliability in identifying various signal conditions such as faults, transients, harmonic distortions, and load variations. The consistent performance improvements across epochs further validate the learning stability and convergence of the model, with accuracy steadily increasing and loss decreasing over time. Moreover, the comprehensive feature extraction across time, frequency, and time-frequency domains enriches the input space, capturing both statistical and spectral properties critical to power signal behavior. The classifier's ability to maintain high performance across different signal types and under various operating conditions underscores its practical applicability in real-world power systems for monitoring, diagnostics, and fault prediction. The integration of intelligent optimization with machine learning creates a powerful, scalable solution capable of handling the complexity of modern power signal processing tasks. The results suggest that SWO-ML is not only accurate but also efficient, offering a valuable tool for smart grid applications and real-time power quality assessment.

6. CONCLUSION

This paper presents a robust and efficient approach for power signal classification using a novel Stacked Whale Optimization-based Machine Learning (SWO-ML) framework. By leveraging comprehensive feature extraction techniques across time, frequency, and time-frequency domains, the model captures critical signal characteristics essential for accurate classification. The integration of SWO effectively reduces feature dimensionality while preserving discriminative power, resulting in enhanced classification accuracy, reduced training time, and improved model generalization. Experimental results demonstrate that the proposed SWO-ML framework significantly outperforms traditional models and other optimization-based approaches in terms of accuracy, precision, recall, and F1-score across various signal types including faults, transients, harmonic distortion, and load variations. The model also shows stable performance improvements over training epochs, further confirming its learning capability and robustness. The proposed system offers a promising and scalable solution for intelligent power signal monitoring and analysis in modern smart grid environments.

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