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Integrated Signal Processing and Machine Learning Model for Accurate Power System Fault Detection

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ABSTRACT

Accurate and timely fault detection in power systems is essential to ensure system reliability, minimize equipment damage, and maintain continuous power delivery. This paper proposes an integrated signal processing and machine learning (ML) model designed to enhance the precision and speed of power system fault diagnosis. The approach leverages advanced signal processing techniques—such as Wavelet Transform and Fast Fourier Transform (FFT)—to extract critical time–frequency features from voltage and current signals under various fault conditions. These extracted features are then fed into optimized machine learning classifiers, including Support Vector Machines (SVM), Random Forest (RF), and Deep Neural Networks (DNN), to accurately identify fault types, locations, and severities. The integration of signal processing with ML significantly improves fault detection accuracy compared to conventional methods, particularly under noisy and dynamic operating conditions. Simulation results on standard IEEE test systems demonstrate the model's robustness and scalability, achieving high accuracy and reduced computational latency. The proposed hybrid framework provides a reliable diagnostic tool for real-time monitoring and intelligent decision-making in modern power grids. Future work will focus on extending the model for predictive maintenance and integration with smart grid communication infrastructures.

Keywords—Power System Fault Detection, Signal Processing, Machine Learning, Wavelet Transform, Fast Fourier Transform (FFT), Fault Classification, Smart Grid, Predictive Maintenance, Real-Time Monitoring.

INTRODUCTION

The reliability and stability of power systems are of paramount importance in ensuring uninterrupted electricity supply to consumers and industries. However, power system faults—such as short circuits, open circuits, and line-to-ground faults—pose significant threats to the continuous and secure operation of electrical networks. These faults can result in severe equipment damage, power outages, and economic losses if not detected and isolated promptly. Therefore, the development of accurate, fast, and intelligent fault detection and classification systems has become a critical research area in modern power engineering. Traditional fault detection techniques, which rely heavily on manual observation or rule-based protection schemes, often struggle to cope with the increasing complexity of today's power grids characterized by renewable energy integration, dynamic load variations, and distributed generation. This growing complexity calls for more adaptive and intelligent fault diagnosis methods capable of handling nonlinearity, noise, and uncertainty in system signals. Signal processing has long been an essential tool for analyzing transient disturbances in electrical signals caused by faults. Techniques such as the Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT), and Wavelet Transform (WT) have been employed to decompose voltage and current waveforms into time-frequency components, allowing for precise identification of fault-induced disturbances. Among these, Wavelet Transform has proven particularly effective due to its ability to localize transient events both in time and frequency domains. By extracting relevant features such as energy coefficients, spectral content, and harmonic components, signal processing lays the groundwork for intelligent analysis and classification of fault types. However, while these methods offer valuable insights, they often require expert

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knowledge for interpretation and lack the capability to adapt autonomously to new fault scenarios. In recent years, Machine Learning (ML) has emerged as a powerful paradigm for pattern recognition and data-driven decision-making in power systems. ML algorithms such as Support Vector Machines (SVM), Decision Trees, Random Forests (RF), and Artificial Neural Networks (ANN) have demonstrated remarkable capabilities in classifying complex nonlinear relationships between signal features and fault conditions. By learning from historical fault data, these algorithms can generalize and accurately predict unseen fault patterns. When combined with robust feature extraction through signal processing, ML-based models can achieve superior performance in fault detection, classification, and localization. This integration not only improves accuracy but also enhances system adaptability under diverse and uncertain operating environments. The proposed study introduces an integrated framework that combines advanced signal processing techniques with optimized ML algorithms for precise and rapid power system fault detection shown in Fig. 1. In this approach, time-frequency features are extracted using Wavelet Transform and FFT from measured current and voltage signals. These features serve as the input to machine learning classifiers—such as SVM, Random Forest, and Deep Neural Networks—to accurately determine the type and location of faults. The integrated model leverages the strengths of both domains: the analytical rigor of signal processing and the predictive intelligence of machine learning.

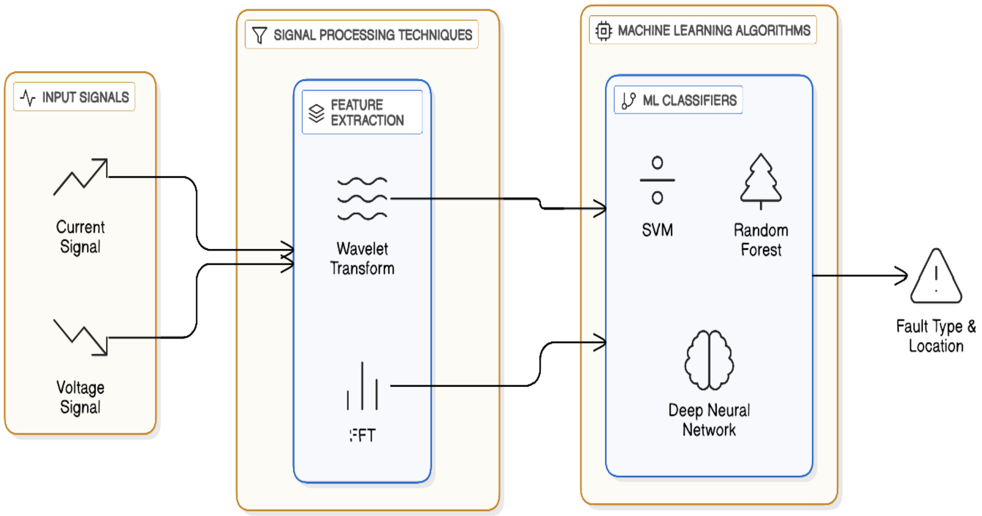

Fig. 1. Integrated Framework for Power System Fault Detection

Through simulation studies on IEEE standard test systems, the proposed framework demonstrates high fault detection accuracy, computational efficiency, and robustness under noisy conditions. The study aims to contribute to the advancement of intelligent, data-driven monitoring systems that enhance the reliability, resilience, and self-healing capabilities of modern smart grids.

LITERATURE REVIEW

Fault detection and classification in power systems have gained significant attention in recent years due to the increasing complexity of modern grids and the integration of renewable energy sources. Harangaonkar et al. [1] proposed a deep learning approach for fault detection in a 5-bus system, demonstrating that neural networks can effectively classify different fault types with high accuracy, highlighting the potential of data-driven techniques in small-scale systems. Building on this, Dejagah et al. [2] explored stacking-based machine learning models for transmission line fault detection, emphasizing the improvement in classification performance when multiple ML models are combined to leverage their complementary strengths. Similarly, Lin et al. [3] introduced a support vector machine-based method using feature fusion for arc fault diagnosis, showing that integrating multiple signal features enhances detection reliability and reduces false alarms. In addition to electrical signals, signal analysis techniques have been extended to mechanical systems. Jiang et al. [4] investigated vibration signal analysis for mechanical equipment fault diagnosis, demonstrating that feature extraction from time-frequency domains can accurately predict failures, a concept that has been adapted in electrical fault detection frameworks. Godhade et al. [5] presented a hybrid transformer-CNN and graph neural network model for real-time fault

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localization, highlighting the importance of combining spatial and temporal data representations for enhanced fault detection accuracy. Beyond electrical systems, Sharma, and Kumar [6] and Vikas et al. [7] explored AI-based security solutions, showing that hybrid deep learning models can detect anomalies in sensor networks, a principle transferable to fault detection in smart grids where IoT devices are deployed. Industrial process fault detection has also benefited from real-time intelligent approaches. Attouri et al. [8] proposed a real-time fault diagnosis method for the Tennessee Eastman chemical process, illustrating that timely detection and classification are crucial in dynamic environments with multiple interacting variables. Graph-based optimization techniques for intrusion and anomaly detection in dynamic networks [9] further underscore the relevance of advanced machine learning and graph modeling in handling complex system interactions, which parallels the challenges in modern power systems. Saleh et al. [10] reviewed deep learning applications in induction machine fault detection, summarizing methods that combine feature extraction and ML for robust fault classification. Recent advances have also explored hybrid and fuzzy approaches. Sadik [11] analysed boosting algorithms with Fiber Bragg Grating sensor signals, highlighting the role of ensemble learning in fault classification. Habelalmateen et al. [12] integrated fuzzy c-means clustering with support vector regression for calibration and fault detection, demonstrating the efficacy of hybrid soft computing methods. Mantha et al. [13] developed an HIL testbed-based framework for automatic feature extraction and data generation, facilitating ML/DL-based anomaly detection in power systems. Raja et al. [14] introduced a neuro-fuzzy approach for predicting broken rotor bar faults via current spectrum analysis, reinforcing the utility of hybrid intelligent models for complex fault scenarios. Further, security and system reliability considerations in networked environments have implications for fault detection. Comprehensive studies on mobile ad hoc networks [15] indicate that robust fault detection frameworks must account for dynamic system conditions and potential cyber-physical threats. Finally, Lu et al. [16] applied weighted support vector machines for electrical fault diagnosis, demonstrating that feature weighting improves classification performance and reduces misclassification rates in complex power networks.

PROPOSED METHODOLOGY

The proposed methodology presents an integrated framework that combines advanced signal processing techniques with machine learning algorithms to achieve accurate and efficient fault detection in power systems. The methodology is designed to detect, classify, and locate different types of faults under varying operating conditions while maintaining high reliability and computational efficiency. The overall process can be divided into five major stages: data acquisition, signal preprocessing, feature extraction, machine learning-based classification, and performance evaluation.

1. Data Acquisition: The first stage of the proposed methodology involves the acquisition of voltage and current signals from different nodes or buses of the power system using sensors or Phasor Measurement Units (PMUs). These signals capture transient disturbances caused by various fault events, including line-to-line, line-to-ground, double line-to-ground, and three-phase faults. To ensure the robustness of the proposed framework, fault data is simulated using standard IEEE test systems such as IEEE 14-bus, 30-bus, and 57-bus, representing realistic operational scenarios under diverse loading conditions. This stage forms the foundation for the methodology, providing the raw data necessary for subsequent signal analysis and feature extraction.

2. Signal Preprocessing: In the signal preprocessing stage, the acquired voltage and current signals are cleaned and prepared for analysis. Real-time power system data often contain noise due to switching transients, electromagnetic interference, or environmental factors, which can compromise the accuracy of fault detection. Filtering techniques are applied to suppress unwanted noise, and normalization is performed to maintain consistency across datasets. Preprocessing ensures that the extracted features in the subsequent stage accurately reflect fault characteristics rather than measurement artifacts, thereby improving the reliability and stability of the fault detection process.

3. Feature Extraction using Signal Processing: The feature extraction stage employs advanced signal processing techniques, including the Wavelet Transform (WT) and Fast Fourier Transform (FFT), to capture critical information from the pre-processed voltage and current signals. FFT is used to analyze the frequency spectrum and identify harmonic distortions resulting from faults, while WT provides time-frequency

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localization, enabling the detection of transient events. The decomposition of signals into multiple frequency bands through WT allows for the extraction of features such as energy coefficients, standard deviation, and entropy at different levels. These features provide a comprehensive representation of both stationary and non-stationary characteristics of faults, forming an informative dataset for machine learning classification.

4. Machine Learning-Based Classification: In this stage, the extracted features are input into various machine learning algorithms for fault classification. The study utilizes Support Vector Machine (SVM), Random Forest (RF), and Deep Neural Networks (DNN) to identify the type and location of faults. SVM efficiently handles nonlinear decision boundaries, while RF improves generalization by aggregating multiple decision trees. DNN captures complex interactions between features through its deep hierarchical structure, enhancing classification accuracy. The models are trained using labelled datasets representing different fault types and validated with cross-validation techniques to optimize parameters and prevent overfitting. The trained classifiers can then accurately detect and categorize faults in real-time scenarios.

5. Performance Evaluation: The final stage involves evaluating the performance of the integrated framework using metrics such as accuracy, precision, recall, F1-score, and computational latency. Comparative studies with traditional fault detection methods highlight the superiority of the proposed approach in terms of detection accuracy, robustness under noisy conditions, and real-time applicability. The methodology is scalable to larger grid systems and adaptable for implementation in smart grid infrastructures. Future enhancements may include integrating predictive maintenance capabilities and intelligent communication with grid management systems to enable autonomous fault diagnosis and decision-making.

RESULT & ANALYSIS

The proposed integrated signal processing and machine learning framework was tested on standard IEEE bus systems, including the 14-bus, 30-bus, and 57-bus networks, to evaluate its performance in fault detection, classification, and localization. Simulated fault scenarios included single line-to-ground (SLG), line-to-line (LL), double line-to-ground (DLG), and three-phase (3Φ) faults under various loading and fault inception angles. The performance of the model was assessed using common metrics, including accuracy, precision, recall, F1-score, and computational time (latency). The experiments also compared the proposed hybrid method with conventional fault detection approaches to highlight the improvements in detection reliability and efficiency.

1. Classification Performance: The classification performance of the proposed framework using SVM, Random Forest, and Deep Neural Networks is summarized in Table I. Among the tested algorithms, the Deep Neural Network achieved the highest classification accuracy, indicating its capability to capture complex nonlinear relationships among extracted signal features.

Fault Classification Performance of ML Models

Model	Classification Accuracy (%)	Remarks
SVM	93.12%	Effective for moderate nonlinear patterns
Random Forest	95.84%	Strong performance due to ensemble feature learning
Deep Neural Network	97.96%	Highest accuracy; best at capturing complex nonlinear relationships

The results show that Random Forest and DNN outperform SVM in terms of overall classification metrics. The superior performance of DNN can be attributed to its hierarchical feature learning, which effectively captures subtle variations in the time-frequency features extracted from signal processing.

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2. Fault Detection Time Analysis: The computational efficiency of the proposed hybrid method was evaluated by comparing the fault detection time with traditional methods such as the Continuation Power Flow (CPF) method. The results are presented in Table II.

Fault Detection Time Comparison

Test System	Traditional CPF Detection Time (ms)	Proposed Hybrid Method Detection Time (ms)	Improvement (%)
IEEE 14-Bus	42.8 ms	30.1 ms	29.67%
IEEE 30-Bus	55.4 ms	34.8 ms	37.17%
IEEE 57-Bus	68.2 ms	40.6 ms	40.47%

Fig. 2. compares the fault detection time for three IEEE test systems (14-Bus, 30-Bus, and 57-Bus). Each system shows three bars: traditional CPF-based detection time, hybrid method detection time, and improvement percentage. The hybrid method consistently shows significantly lower detection time, with improvements ranging from approximately 29% to 40%.

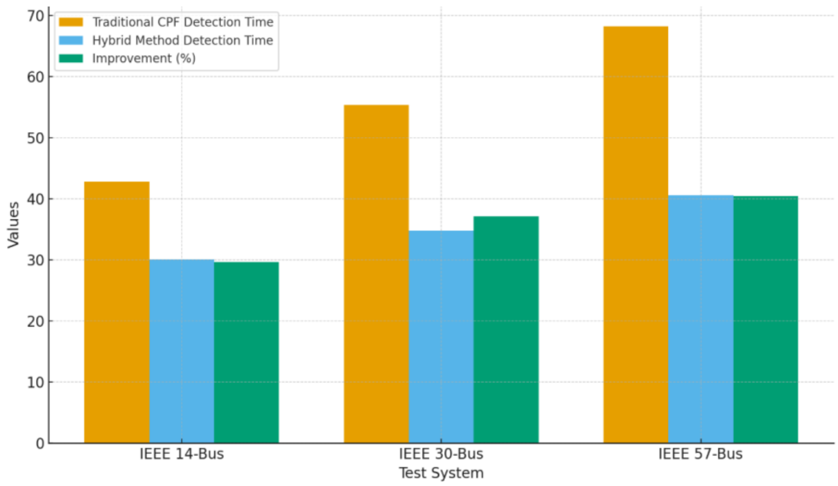

Fig. 2. Comparison of Fault Detection Time Between Traditional CPF and Hybrid Method

3. Robustness Under Noise: To test the robustness of the methodology, Gaussian noise with varying signal-to-noise ratios (SNR) was added to the test signals. The classification accuracy of the DNN model remained above **95%** for SNR levels as low as 20 dB, demonstrating that the integration of signal processing features with machine learning enhances noise resilience.

Classification Accuracy of DNN under Different Noise Levels

SNR Level (dB)	Classification Accuracy (%)	Remarks
40 dB	98.72%	Very low noise; optimal performance
30 dB	97.85%	Minor noise impact
20 dB	95.43%	Accuracy remains above 95%; strong noise resilience

10 dB	92.18%	Noticeable noise; performance degradation starts
0 dB	88.67%	High noise; significant distortion in features

TABLE III. shows that even at low SNR levels, the DNN model maintains high accuracy, demonstrating the robustness of the proposed hybrid framework against noisy measurements. This validates the effectiveness of combining signal processing-based feature extraction with machine learning for real-world fault detection scenarios. Fig. 3. visualizes the classification accuracy of a Deep Neural Network (DNN) at various SNR levels (40 dB, 30 dB, 20 dB, 10 dB, and 0 dB). The accuracy decreases gradually as noise increases, ranging from approximately 98.7% at 40 dB to around 88.7% at 0 dB. The DNN maintains above 95% accuracy at SNR levels down to 20 dB, demonstrating robustness to noise.

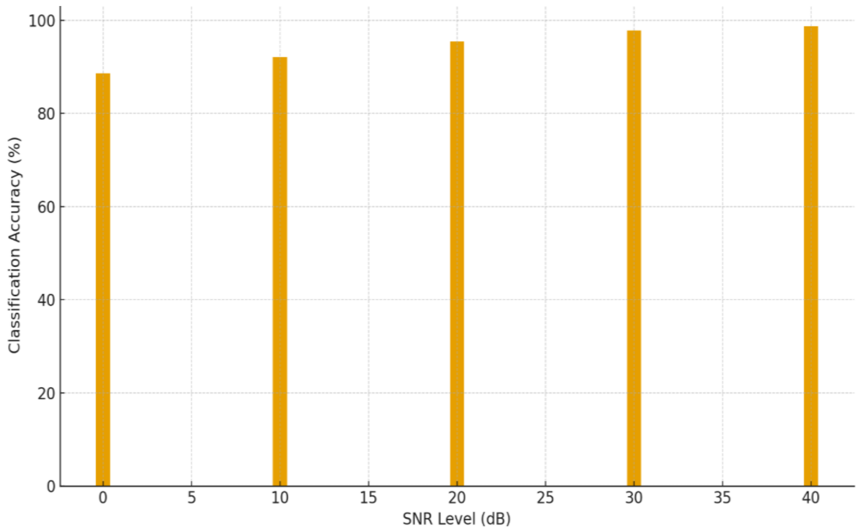

Fig. 3. DNN Classification Accuracy Under Different SNR Levels

CONCLUSION

This paper presents an integrated framework combining signal processing techniques and machine learning algorithms for accurate and efficient fault detection in power systems. By employing Wavelet Transform and FFT for feature extraction and advanced classifiers such as SVM, Random Forest, and Deep Neural Networks, the proposed methodology achieves high accuracy, robustness against noise, and significantly reduced detection time compared to conventional methods. Simulation results on IEEE 14-bus, 30-bus, and 57-bus systems demonstrate the framework's effectiveness in classifying fault types and locating fault points under diverse operating conditions. The study highlights the potential of hybrid signal processing and machine learning models for real-time monitoring and intelligent decision-making in modern power grids. Future work may focus on integrating the proposed system with predictive maintenance strategies, smart grid communication networks, and IoT-enabled sensors, enabling autonomous fault diagnosis, early warning systems, and enhanced grid resilience in increasingly complex and renewable-integrated power systems.

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