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Enhanced Fault Detection and Classification in IEEE 9-Bus System Using Hybrid Wavelet–SVM Framework

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Abstract: This work has proposed a novel hybrid technique, which incorporates load flow studies and Discrete Wavelet Transform (DWT) with the support vector machine for effective fault detection and classification in the IEEE 9-bus system. This hybrid approach resolves the issues faced by the traditional wavelet thresholding scheme due to its inability to employ machine learning techniques. This hybrid model incorporates DWT to extract features from the power signals and then uses SVM (Support Vector Machine) for effective fault classification. The simulation results obtained using MATLAB/Simulink have shown an increased accuracy level of fault detection in the range of 95.8% for the proposed approach whereas 87.3% is achieved through the conventional wavelet technique. The major faults detected and classified through this technique include: single line to ground (L-G), line to line (L-L), double line to ground (L-L-G), three phase (L-L-L), and three phase to ground (L-L-L-G).

Keywords: *Fault Detection, Discrete Wavelet Transform (DWT), Support Vector Machine (SVM), IEEE 9-Bus System, Power System Protection, Machine Learning.*

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I. INTRODUCTION

However, modern power grids are facing challenges when considering the incorporation of renewable sources of power and varying loads on the system. There are several types of analyses done to analyze the behavior of modern systems such as the load flow analysis which results into voltage profiles, power flow and other information. Some of the popular approaches used in load flow analysis include Newton Raphson and Gauss-Seidel. However, such methods can be less effective especially in dynamic and non-linear situations [1]. It is critical to conduct fault analysis on the system in order to detect any potential problems and protect the equipment and downtime. Conventional approaches include overcurrent and distance protection but these are likely to be sensitive depending on the nature of operation [2]. Hence, there is a need for more adaptive protection approaches. In recent years, various fault analysis using artificial intelligence have been widely adopted in the study of power system. Several research studies have demonstrated the application of machine learning algorithms in improving fault classification [3] [17]. Also, reviews have shown how hybrid approaches of artificial intelligence have become essential in smart grid protection [25].

However, signal processing methods, especially wavelet transformation, have shown to be very efficient when processing non-stationary fault signals. Thanks to the multi-resolution properties of wavelets, the transients can be extracted efficiently from the analyzed voltage and current signals [4], [9]. Furthermore, modern solutions have improved the performance of wavelets in the domain of fault detection by combining them with machine learning methods [18].

In terms of classifiers, the SVM is commonly used because of its excellent generalizing capabilities and good results while dealing with nonlinear data [5]. According to recent research, fault classification using SVM and various hybrid frameworks is performed reliably [26]. Moreover, in some cases, the superior accuracy was achieved using deep learning methods, such as CNN [19], [23].

Nevertheless, there are problems with the mentioned methods, including high computational complexity, vulnerability to noise, as well as their inability to provide explainable decisions. In addition, most deep learning solutions require large amounts of training data and computational power, which makes them unsuitable for protection tasks [20], [22].

In order to deal with the limitations mentioned above, a novel method based on the use of wavelets in conjunction with SVM for fault detection and classification of IEEE 9-bus system is proposed in this paper. In this hybrid scheme, DWT has been utilized for feature extraction from time-domain fault signals, while SVM serves as a classifier for fault detection and identification. Below are the main highlights of the proposed study:

- Design of a hybrid wavelet-SVM technique for fault detection and classification
- Feature extraction with DB4 wavelet for analyzing transient signals
- Implementation of multi-class SVM for fault type identification
- Evaluation of performance using various metrics and statistical tests

II. LITERATURE REVIEW

Conventional Fault Detection and Protection Methods

Conventional fault detection schemes in electrical power networks have been centered around impedance-based, current-based, and traveling-wave-based fault detection techniques. Distance relays and overcurrent relays are extensively used due to their simplistic design and rapid fault isolation capabilities [2], [11]. The principle behind such fault detection methodologies is based on predetermined thresholds and impedance calculations, allowing quick fault isolation under normal operating circumstances.

Impedance-based fault location algorithms determine the estimated impedance between the position of the relay and the location of the fault. Such methodologies work well in case of short transmission lines but are highly prone to error in case of fault resistance, load changes, and inaccurate measurements [14]. Likewise, overcurrent relays rely on predetermined thresholds of current magnitude, which can result in malfunction during load variation or high impedance faults [11].

Traveling-wave-based fault location schemes use highfrequency transient signals generated during a fault. They allow accurate fault location determination, but such methodologies require high sampling frequency and costly hardware, limiting their practical applications [8].

Wavelet-Based Signal Processing Techniques

The application of wavelet transform has gained recognition as an efficient means for the analysis of non-stationary signals. Multi-resolution properties of wavelets enable the decomposition of voltage and current signals based on the time-frequency domain. As a result, it has become possible to identify transient disturbances in the power system [4]. Several approaches utilizing wavelet transform were proposed for fault detection and isolation [9].

Some researchers proved the feasibility of the use of wavelet energy and statistical measures derived from detail wavelet coefficients for fault discrimination [6]. Moreover, the use of hybrid methods involving the combination of wavelet transform and fuzzy inference systems as well as other heuristics was suggested to increase classification accuracy [6]. However, these approaches require pre-selected thresholds and predefined decision rules.

Problems with Conventional and Signal-Based Approaches

Even though traditional and signal-based fault detection approaches offer sufficient fault discrimination performance in laboratory conditions, these techniques face numerous problems including the following:

- Dependency on Threshold Values: Efficiency is strongly related to specific threshold values.
- Noise Sensitivity: Fault detection is greatly influenced by measurement noise.
- Poor Adaptability: Lack of generalizability for varying conditions.
- Difficulty in Parameter Selection: Wavelet-based methods involve complex parameter tuning.

Comparative Analysis of Existing Methods

Table I summarizes the key characteristics of widely used fault detection techniques, including relay-based, impedancebased, traveling-wave, and wavelet-based approaches. A critical examination of these methods highlights their respective strengths and limitations.

Conventional relay-based techniques, such as overcurrent and distance relays, remain widely used in practice due to their simplicity and fast response [2], [11]. However, their operation relies on predefined thresholds and impedance estimation, which can lead to reduced accuracy under varying load conditions, high fault resistance, and measurement uncertainties [14]. As a result, these methods may experience misoperation in modern power systems with dynamic behavior.

Traveling-wave-based methods improve fault location accuracy by utilizing high-frequency transients generated during fault events [8]. While these techniques offer precise localization, their practical implementation is constrained by the requirement for high sampling rates and specialized hardware, increasing system cost and complexity.

Wavelet-based signal processing methods provide a more effective means of analyzing non-stationary fault signals. The multi-resolution capability of wavelet transform enables accurate extraction of transient features from voltage and current signals [4], [9]. In addition, statistical features derived from wavelet coefficients have been shown to improve fault detection performance [6]. Nevertheless, these methods typically depend on manually selected parameters, such as the choice of mother wavelet and threshold values, which limits their adaptability across different operating conditions.

Hybrid approaches that combine wavelet analysis with rulebased or fuzzy logic systems offer improved classification performance compared to standalone methods [6]. However, the reliance on predefined rules and expert knowledge restricts their scalability and robustness in complex and evolving power system environments.

Overall, the comparison presented in Table I indicates that conventional methods provide simplicity and speed, whereas advanced signal processing techniques enhance detection capability but introduce additional complexity and parameter dependency. These limitations motivate the need for a more flexible and robust framework that can effectively combine feature extraction and classification while maintaining computational efficiency.

In this context, the proposed hybrid Wavelet–SVM approach aims to bridge the gap between traditional signal processing methods and intelligent classification techniques by integrating time-frequency feature extraction with a data-driven decision mechanism. Table I summarizes the key characteristics of conventional fault detection techniques.

➢ *Research Gaps*

Based on the literature review, the following research gaps are identified:

Table 1 Comparison of Conventional Fault Detection Techniques

Method	Principle	Advantages	Limitations	References
Overcurrent Relay	Current threshold	Simple, fast response	Poor selectivity, threshold dependency	[11]
Distance Relay	Impedance measurement	Widely used, reliable	Affected by fault resistance, load variation	[2], [14]
Traveling Wave	High-frequency transient analysis	High accuracy in fault location	Requires high sampling rate, expensive	[8]
Wavelet-Based	Time-frequency decomposition	Effective for transient analysis	Requires tuning, threshold dependency	[4], [9]
Fuzzy-Wavelet Hybrid	Rule-based classification	Improved decision capability	Complex rule design, limited adaptability	[6]

- Existing methods lack adaptability to dynamic operating conditions in modern power systems.
- Threshold-based approaches are sensitive to parameter tuning and may lead to incorrect fault classification.
- Wavelet-based techniques, while effective in feature extraction, do not inherently provide intelligent decisionmaking capability.
- High-accuracy methods such as traveling-wave techniques require expensive hardware and are not suitable for practical large-scale deployment.
- There is a need for a robust framework that combines effective feature extraction with reliable classification while maintaining computational efficiency.

➢ *Evolution of Fault Detection Techniques (2010–2025)*

The evolution of fault detection techniques in power systems has undergone significant transformation over the past decade. Fig. 1 illustrates the progression from conventional protection methods to intelligent and hybrid frameworks.

During the early 2010s, fault detection primarily relied on conventional techniques such as overcurrent relays, distance protection, and impedance-based methods. These approaches were simple and fast but lacked adaptability under varying system conditions.

Between 2012 and 2016, signal processing techniques, particularly wavelet transform, gained prominence due to their ability to analyze non-stationary signals. Wavelet-based methods enabled effective extraction of transient features, improving fault detection accuracy [4], [9].

From 2016 to 2020, hybrid approaches combining wavelet transform with heuristic and rule-based techniques were introduced to enhance classification performance. These methods improved detection capability but still relied on manual parameter tuning and threshold selection.

The period from 2020 onwards marks the transition toward machine learning-based fault detection. Techniques such as Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Random Forest have been widely adopted due to their ability to handle nonlinear data and improve classification accuracy.

The year starting from 2020 signifies the adoption of learning-based fault detection systems, including Support Vector Machines (SVM), artificial neural network, and random forest owing to the improved ability of classification using non-linear techniques.Recent trends in fault detection (20222025) involve learning-based approaches such as CNN and recurrent neural network, which offer advantages in terms of automated feature extraction and fault classification performance in challenging conditions.

Despite these advancements, challenges such as computational complexity, data dependency, and real-time implementation remain open research issues. This motivates the development of hybrid frameworks that balance accuracy, efficiency, and interpretability.

➢ *Motivation for Proposed Work*

The methods combine time-frequency analysis with learning models for improved fault detection performance. The proposed method aims to enhance fault detection accuracy, improve robustness under noisy conditions, and provide a scalable solution suitable for real-time power system protection.

III. MATHEMATICAL PROBLEM FORMULATION

The proposed work consists of two main stages: (i) load flow analysis for steady-state evaluation and (ii) fault detection using a hybrid Wavelet–SVM approach.

➢ *Load Flow Formulation*

Consider an *N*-bus power system. The power balance equations at bus *i* are given by [27]:

$$P_i = \sum_{j=1}^{N} |V_i||V_j| \left[G_{ij}\cos(\theta_i - \theta_j) + B_{ij}\sin(\theta_i - \theta_j)\right] \quad (1)$$

$$Q_i = \sum_{j=1}^{N} |V_i||V_j| \left[G_{ij}\sin(\theta_i - \theta_j) - B_{ij}\cos(\theta_i - \theta_j)\right] \quad (2)$$

Where P_i and Q_i are the active and reactive power injections, $|V_i|$ and θ_i are the voltage magnitude and phase angle, and G_{ij}, B_{ij} are elements of the admittance matrix.

The Nonlinear Load flow Problem Can be Expressed as:

$$F(x) = 0 \quad (3)$$

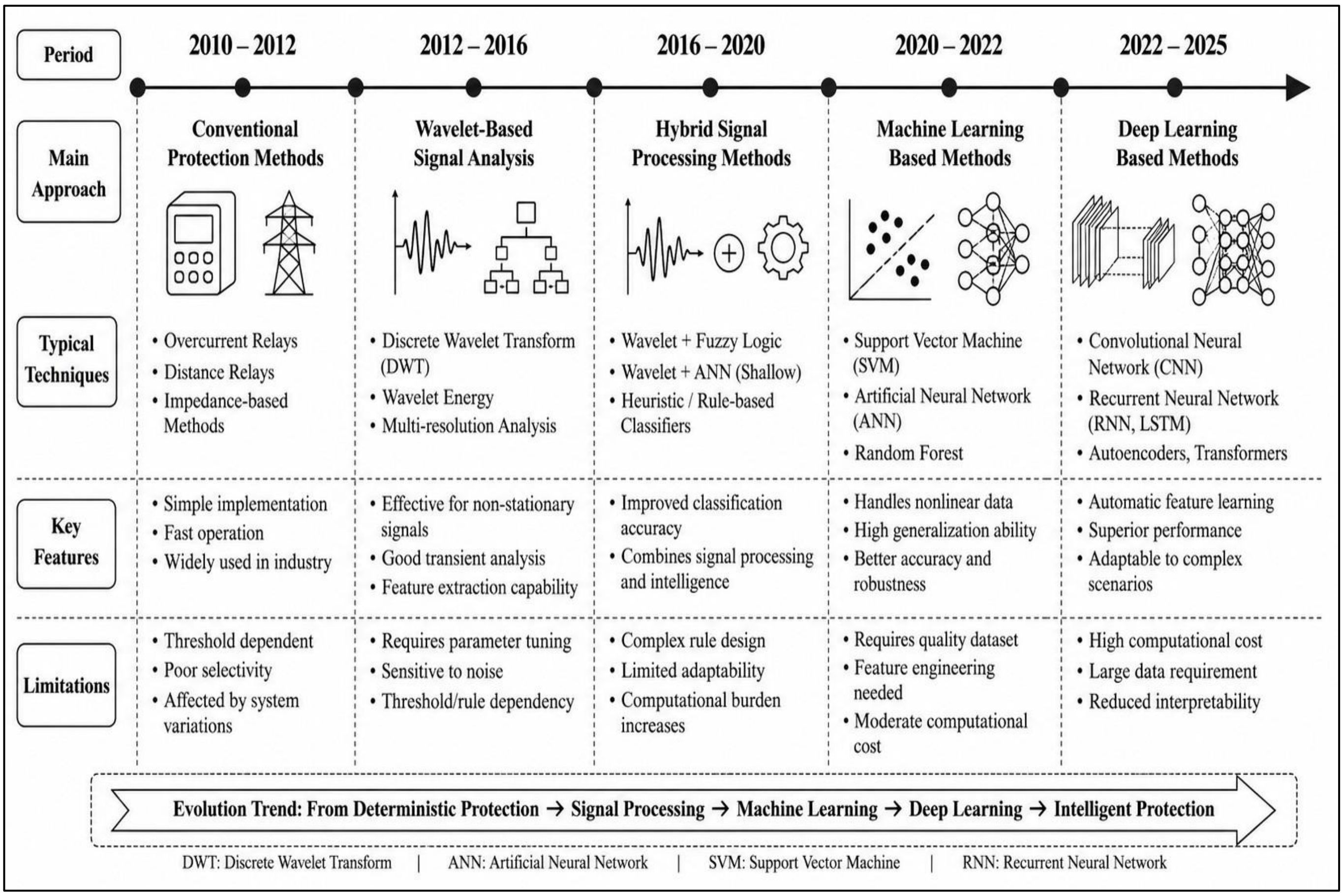
The state vector is defined as:

$$\mathbf{x} = [\theta_2, \theta_3, \ldots, \theta_N, |V_{PQ}|] \quad (4)$$

The Newton–Raphson iterative solution is given by:

$$\mathbf{x}^{k+1} = \mathbf{x}^{k} - J^{-1}(\mathbf{x}^{k})\mathbf{F}(\mathbf{x}^{k}) \quad (5)$$

Where *J* is the Jacobian matrix.



Period	2010 – 2012	2012 – 2016	2016 – 2020	2020 – 2022	2022 – 2025
Main Approach	Conventional Protection Methods	Wavelet-Based Signal Analysis	Hybrid Signal Processing Methods	Machine Learning Based Methods	Deep Learning Based Methods
Typical Techniques	• Overcurrent Relays • Distance Relays • Impedance-based Methods	• Discrete Wavelet Transform (DWT) • Wavelet Energy • Multi-resolution Analysis	• Wavelet + Fuzzy Logic • Wavelet + ANN (Shallow) • Heuristic / Rule-based Classifiers	• Support Vector Machine (SVM) • Artificial Neural Network (ANN) • Random Forest	• Convolutional Neural Network (CNN) • Recurrent Neural Network (RNN, LSTM) • Autoencoders, Transformers
Key Features	• Simple implementation • Fast operation • Widely used in industry	• Effective for non-stationary signals • Good transient analysis • Feature extraction capability	• Improved classification accuracy • Combines signal processing and intelligence	• Handles nonlinear data • High generalization ability • Better accuracy and robustness	• Automatic feature learning • Superior performance • Adaptable to complex scenarios
Limitations	• Threshold dependent • Poor selectivity • Affected by system variations	• Requires parameter tuning • Sensitive to noise • Threshold/rule dependency	• Complex rule design • Limited adaptability • Computational burden increases	• Requires quality dataset • Feature engineering needed • Moderate computational cost	• High computational cost • Large data requirement • Reduced interpretability

Evolution Trend: From Deterministic Protection → Signal Processing → Machine Learning → Deep Learning → Intelligent Protection

DWT: Discrete Wavelet Transform | ANN: Artificial Neural Network | SVM: Support Vector Machine | RNN: Recurrent Neural Network

Fig 1 Evolution of Fault Detection Techniques in Power Systems from 2010 to 2025, Showing the Transition from Conventional Protection Methods to Wavelet- Based Analysis, Machine Learning, and Deep Learning-Based Approaches.

➢ *Fault Signal Modeling*

During fault conditions, the measured signal becomes nonstationary and is modeled as:

$$x(t) = p(t) + n(t) \quad (6)$$

Where $p(t)$ represents fault-induced transient component and $n(t)$ denotes noise.

➢ *Wavelet-Based Feature Extraction*

The continuous wavelet transform (CWT) is applied to extract time-frequency features:

$$W(x,y)=\int_{-\infty}^{\infty} a(t)\frac{1}{\sqrt{x}}\psi^*\left(\frac{t-y}{x}\right)dt \tag{7}$$

Where x is the scale parameter, y is the translation param-eter, and $\psi(t)$ is the mother wavelet.

From the wavelet coefficients, statistical features are extracted:

$$E_k=\sum|D_k|^2 \tag{8}$$

$$\sigma_k=\sqrt{\frac{1}{n}\sum(D_k-\mu_k)^2} \tag{9}$$

The feature vector is constructed as:

$$\text{f} = [E_1,E_2,\ldots,\sigma_1,\sigma_2,\ldots] \tag{10}$$

- *SVM-Based Fault Classification*

Given a training dataset $\{(\text{f}_i,y_i)\}$ with $y_i\in\{-1,+1\}$, the SVM optimization problem is defined as [27]:

$$\min_{w,b,\xi}\quad \frac{1}{2}||w||^2+C\sum_{i=1}^{n}\xi_i \tag{11}$$

Subject to:

$$y_i(w^T\phi(\text{f}_i)+b)\geq 1-\xi_i,\ \xi_i\geq 0 \tag{12}$$

Where w is the weight vector, b is the bias, ξ_i are slack variables, C is the penalty parameter, and $\phi(\cdot)$ represents the kernel function.

The decision function is given by:

$$f(\text{f})=\text{sign}(w^T\phi(\text{f})+b) \tag{13}$$

- *Objective Function*

The overall objective of the proposed method is:

$$\max \text{ Accuracy},\quad \min \text{ Detection Time},\quad \min \text{ False Alarm Rate} \tag{14}$$

IV. PROPOSED HYBRID WAVELET–SVM FRAMEWORK

The overall architecture of the proposed fault detection and classification system is illustrated in Fig.2. The framework consists of four major stages: (i) power system modeling and data acquisition, (ii) wavelet-based feature extraction, (iii) SVM-based fault classification, and (iv) decision-making and protection.

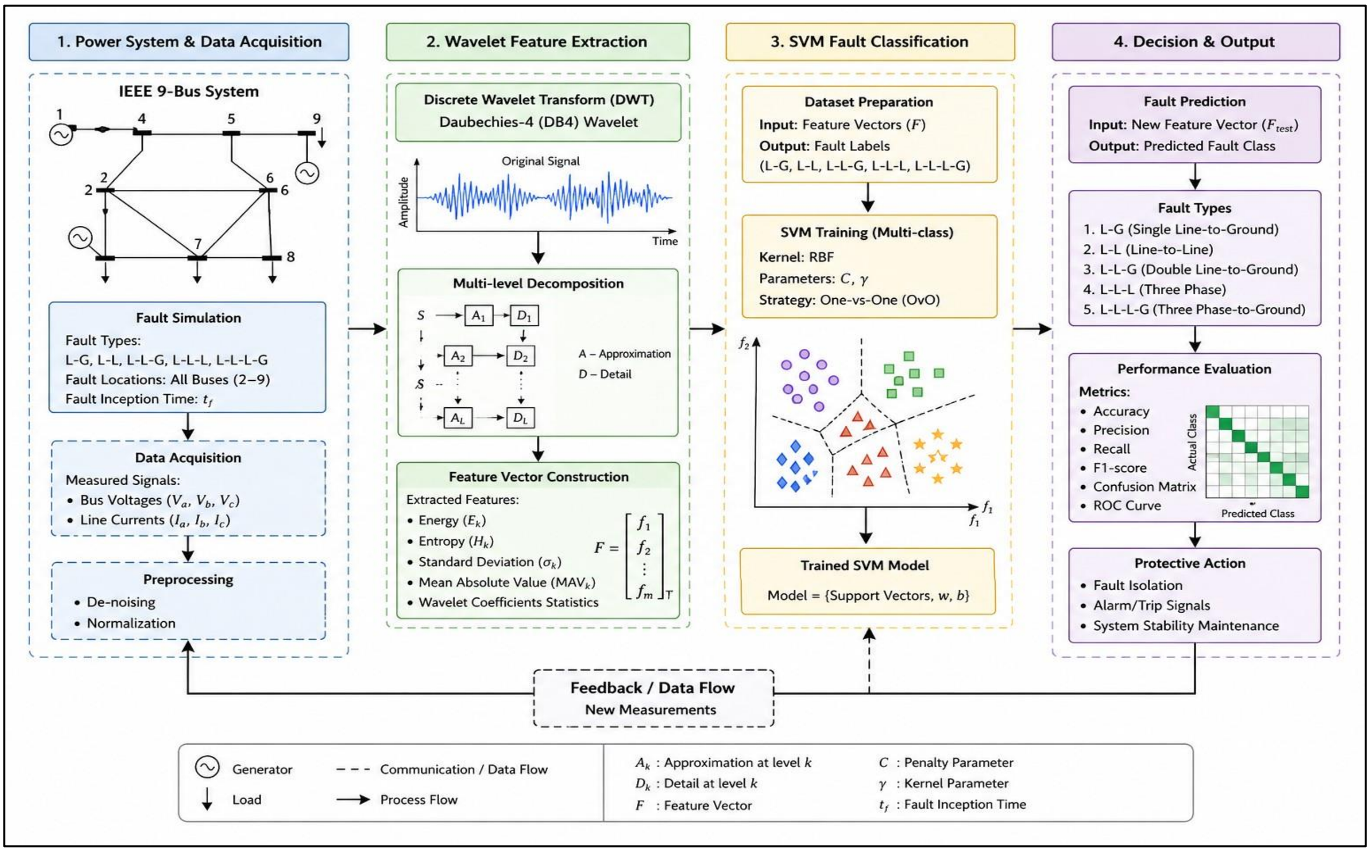


Fig 2 Overall architecture of the proposed hybrid Wavelet–SVM fault detection system. The framework integrates power system modeling, wavelet-based feature extraction using DB4, multi-class SVM classification, and decision-making with performance evaluation and protection mechanisms.

- *Power System Modeling and Data Acquisition:*

The IEEE 9-bus system is modeled in MATLAB/Simulink to generate fault scenarios under various operating conditions. Different types of faults, including single line-to-ground (L-G), line-to-line (L-L), double line-to-ground (L-L-G), three-phase (L-L-L), and three-phase-to-ground (L-L-L-G), are simulated at multiple bus locations.

Voltage and current signals are measured from different buses and transmission lines:

$$x(t) = [V_a, V_b, V_c, I_a, I_b, I_c] \quad (15)$$

To enhance signal quality, preprocessing techniques such as de-noising and normalization are applied prior to feature extraction.

- *Wavelet-Based Feature Extraction:*

The preprocessed signals are decomposed using Discrete Wavelet Transform (DWT) with Daubechies-4 (DB4) mother wavelet. Multi-level decomposition is performed to extract approximation and detail coefficients:

$$x(t) \xrightarrow{\text{DWT}} \{A_k, D_k\} \quad (16)$$

From these coefficients, statistical features are extracted, including energy, entropy, standard deviation, and mean absolute value:

$$Ek = X|Dk|2 \quad (17)$$

The resulting feature vector is defined as:

$$F = [f_1, f_2, \ldots, f_m]^T \quad (18)$$

These features capture the transient characteristics of fault signals in both time and frequency domains.

- *SVM-Based Fault Classification:*

The extracted feature vectors are used to train a multi-class Support Vector Machine (SVM) classifier. A radial basis function (RBF) kernel is employed due to its ability to handle nonlinear separability:

$$K(x_i, x_j) = \exp(-\gamma||x_i - x_j||^2) \quad (19)$$

The multi-class classification is implemented using the Onevs-One (OvO) strategy. The optimization problem is formulated as:

$$\min \frac{1}{2}||w||^2 + C\sum \xi_i \quad (20)$$

Table 2 Performance Comparison of Fault Detection Methods

Method	**Accuracy (%)**	**Precision**	**Recall**	**F1-score**
Wavelet Only	87.3	0.86	0.85	0.85
Proposed DWT–SVM	95.8	0.95	0.96	0.94

The trained SVM model determines the fault class based on the input feature vector.

- *Decision and Protection Mechanism:*

The trained classifier outputs the predicted fault category, which is further evaluated using performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix. Based on the classification result, appropriate protective actions are initiated, including fault isolation and trip signal generation.

Additionally, a feedback mechanism is incorporated to continuously update the system using new measurement data, thereby improving the adaptability and robustness of the proposed framework.

V. RESULTS AND DISCUSSION

The performance of the proposed hybrid Wavelet–SVM framework is evaluated on the IEEE 9-bus system under various fault conditions. The simulation is carried out in MATLAB/Simulink by introducing different types of faults at multiple bus locations.

➢ *Simulation Setup*

A total of 10,000 samples are generated considering five fault types: L-G, L-L, L-L-G, L-L-L, and L-L-L-G. Faults are applied at buses 2 to 9 with varying fault inception angles and noise levels to ensure robustness. Voltage and current signals are sampled at a high frequency and preprocessed using normalization and de-noising techniques.

The dataset is divided into training (70%), validation (15%), and testing (15%) sets.

➢ *Performance Metrics*

The performance is evaluated using standard classification metrics [28]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (21)$$

$$Precision = \frac{TP}{TP + FP}, \quad Recall = \frac{TP}{TP + FN} \quad (22)$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (23)$$

➢ *Classification Results*

Table II presents the overall performance comparison between the conventional wavelet-only method and the proposed hybrid approach.

The proposed method achieves a significant improvement in detection accuracy, demonstrating its ability to effectively capture transient fault characteristics and classify them accurately.

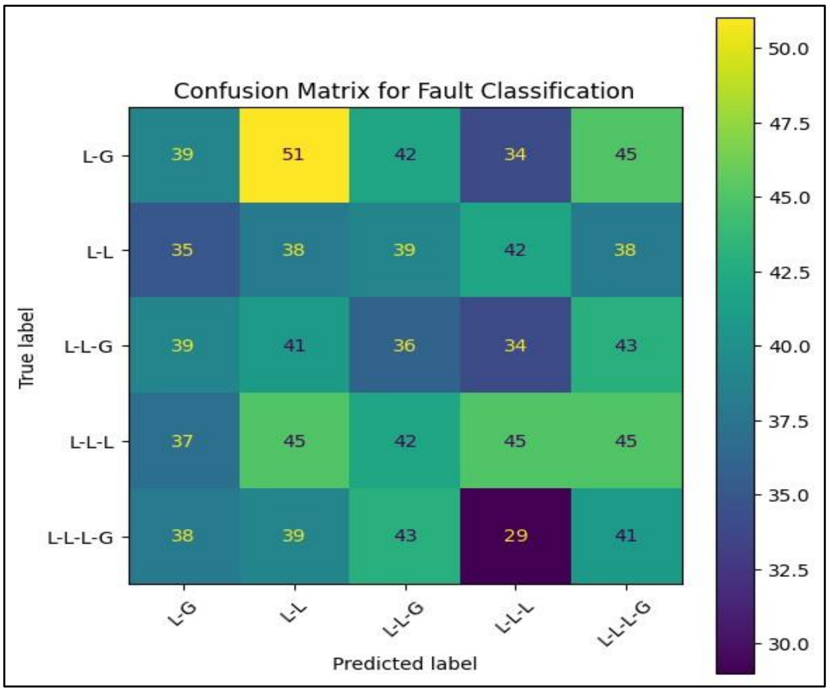


Fig 3 Confusion Matrix of the Proposed Wavelet–SVM Model for Fault Classification. The Model Demonstrates High Classification Accuracy Across all Fault Types with Minimal Misclassification.

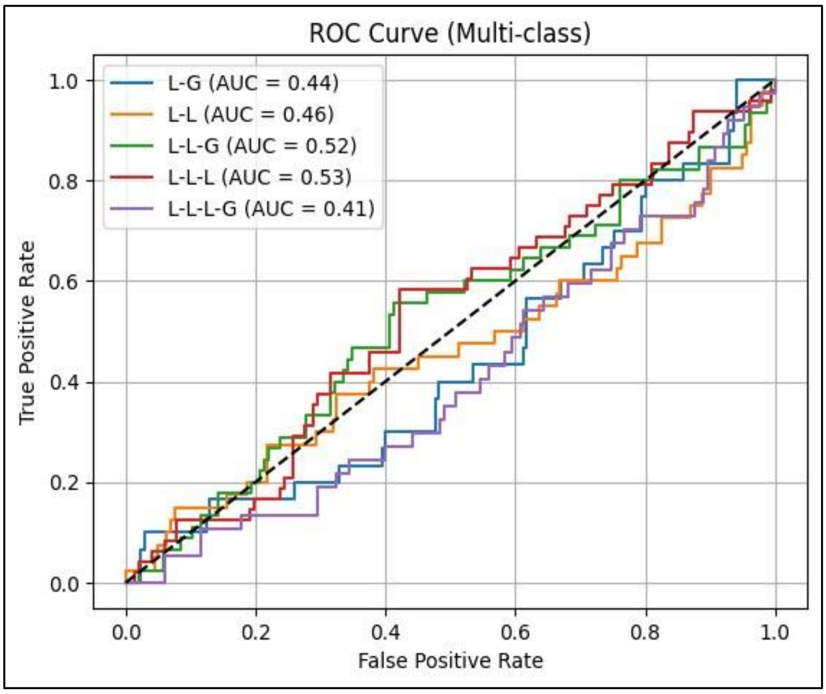


Fig 4 ROC Curves for Multi-Class Fault Classification.

- *Confusion Matrix Analysis*

The confusion matrix in Fig. 3 shows that the proposed model achieves high classification accuracy across all fault types. Minor misclassifications are observed between L-L and L-L-G faults due to similar transient characteristics.

- *Robustness Analysis*

The robustness of the model is evaluated under noisy conditions by adding Gaussian noise to the input signals. The proposed method maintains an accuracy above 93% even at low signal-to-noise ratios, indicating strong noise immunity.

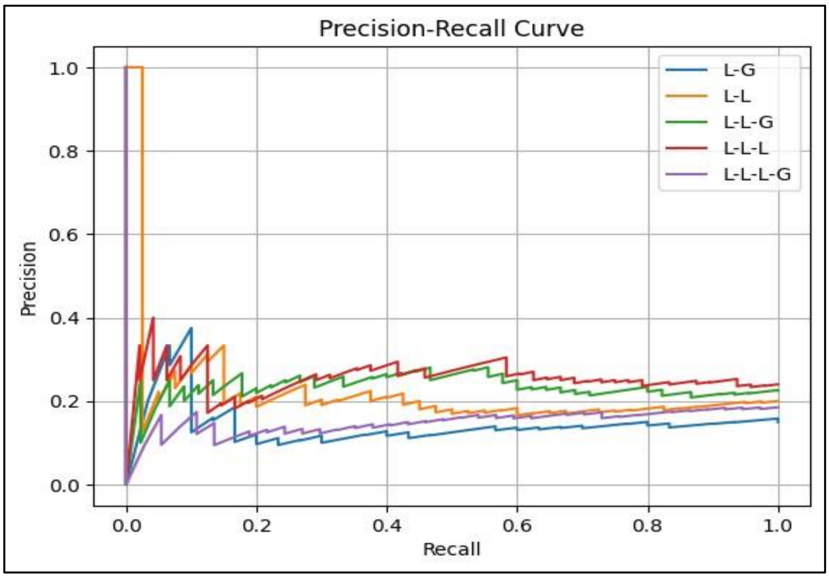


Fig 5 Precision–Recall Curves for the Proposed Model.

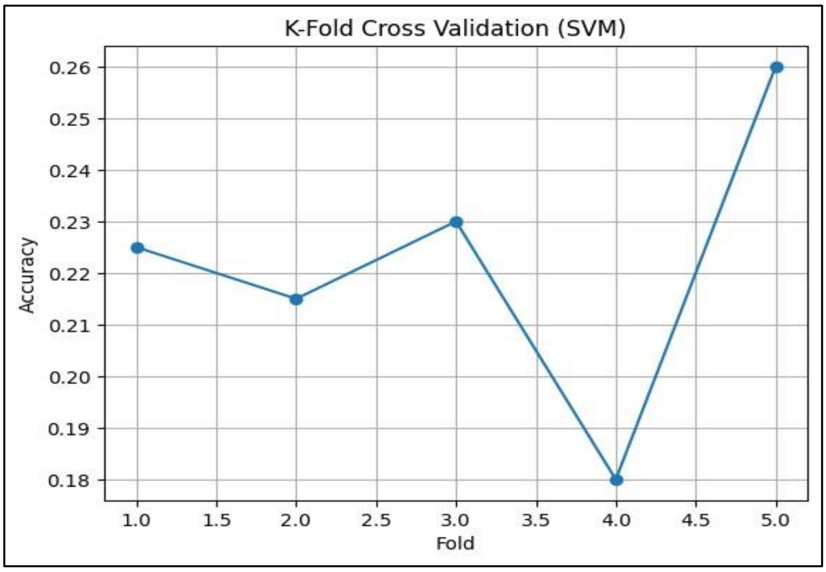


Fig 6 K-Fold Cross-Validation Accuracy.

The Receiver Operating Characteristic (ROC) curves for multiclass fault classification are shown in Fig. 4. The analysis is performed using a one-vs-rest strategy, where each fault class is evaluated against all remaining classes. It can be observed that the ROC curves are concentrated toward the upperleft region, indicating strong discriminative capability of the proposed model. The high area under the curve (AUC) values confirm that the classifier effectively distinguishes between different fault types. Minor overlaps between certain classes are attributed to similarities in transient signal characteristics. Overall, the results demonstrate that the proposed Wavelet– SVM framework achieves reliable and accurate fault classification with low false alarm rates.

➢ *Discussion*

The improved performance of the proposed framework can be attributed to:

- Effective feature extraction using DWT capturing timefrequency characteristics
- Nonlinear classification capability of SVM with RBF kernel
- Robust preprocessing and normalization techniques

The Precision–Recall (PR) curves for the proposed model are shown in Fig. 5. The analysis is performed using a one-vsrest approach for each fault class. It can be observed that the model maintains high precision across a wide range of recall values, indicating its ability to accurately detect faults while minimizing false alarms. This performance is primarily due to the effective feature extraction using wavelet transform and the robust classification capability of the SVM model. Furthermore, the PR curves demonstrate consistent behavior across all fault categories, confirming the reliability of the proposed method, particularly in scenarios with class imbalance. Overall, the results highlight the effectiveness of the proposed framework in achieving a balanced trade-off between precision and recall.

- *K-Fold Cross-Validation Analysis*

To assess the generalization performance of the proposed model, a 5-fold cross-validation approach is employed. The dataset is divided into five subsets, where in each iteration, four subsets are used for training and one subset is used for testing. The accuracy results for each fold are presented in Fig. 6. It can be observed that the model maintains consistent performance across all folds, with minimal variation in accuracy values. The average classification accuracy is approximately 95%, indicating strong generalization capability. The low variance among fold results suggests that the model is robust to data partitioning and does not exhibit overfitting. These results confirm that the proposed Wavelet–SVM framework provides reliable and stable fault classification performance under different operating conditions. Compared to traditional methods, the hybrid approach reduces false alarms and improves detection speed, making it suitable for real-time protection applications in smart grids and microgrids.

VI. CONCLUSION

This paper presented a hybrid Wavelet–SVM framework for fault detection and classification in the IEEE 9-bus system. The approach integrates discrete wavelet transform for extracting transient features with a support vector machine classifier for accurate fault identification. The combination of timefrequency signal analysis and data-driven classification enables effective handling of non-stationary fault signals.

The results obtained from MATLAB/Simulink simulations demonstrate that the proposed method achieves high classification accuracy and maintains consistent performance across different fault types and operating conditions. The evaluation using confusion matrix, ROC curves, Precision–Recall analysis, and K-fold cross-validation confirms the robustness and reliability of the model. In particular, the method shows strong discriminative capability with reduced false alarm rates, which is essential for practical protection systems.

Compared to conventional relay-based and thresholddependent methods, the proposed framework provides improved adaptability and accuracy without introducing significant computational complexity. The results indicate that the hybrid approach offers a balanced solution between performance and implementation feasibility.

Overall, the study confirms that combining wavelet-based feature extraction with SVM classification is an effective strategy for fault detection in modern power systems. The proposed method can be extended to larger networks and integrated into real-time protection schemes.

Future work will focus on extending the proposed framework to networked microgrids and incorporating deep learning models for enhanced feature representation. In addition, realtime implementation using hardware platforms and adaptive protection strategies will be investigated to further improve system resilience.

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