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ARTICLE

Active Fault Diagnosis and Early Warning Model of Distribution Transformers Using Sample Ensemble Learning and SO-SVM

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ABSTRACT: Distribution transformers play a vital role in power distribution systems, and their reliable operation is crucial for grid stability. This study presents a simulation-based framework for active fault diagnosis and early warning of distribution transformers, integrating Sample Ensemble Learning (SEL) with a Self-Optimizing Support Vector Machine (SO-SVM). The SEL technique enhances data diversity and mitigates class imbalance, while SO-SVM adaptively tunes its hyperparameters to improve classification accuracy. A comprehensive transformer model was developed in MATLAB/Simulink to simulate diverse fault scenarios, including inter-turn winding faults, core saturation, and thermal aging. Feature vectors were extracted from voltage, current, and temperature measurements to train and validate the proposed hybrid model. Quantitative analysis shows that the SEL–SO-SVM framework achieves a classification accuracy of 97.8%, a precision of 96.5%, and an F1-score of 97.2%. Beyond classification, the model effectively identified incipient faults, providing an early warning lead time of up to 2.5 s before significant deviations in operational parameters. This predictive capability underscores its potential for preventing catastrophic transformer failures and enabling timely maintenance actions. The proposed approach demonstrates strong applicability for enhancing the reliability and operational safety of distribution transformers in simulated environments, offering a promising foundation for future real-time and field-level implementations.

KEYWORDS: Core saturation; distribution transformer; early fault detection; ensemble learning; fault diagnosis; inter-turn fault; MATLAB simulation; sample ensemble learning; self-optimizing SVM; transformer protection

1 Introduction

1.1 Motivation and Background

Distribution transformers serve as critical components in electrical power distribution networks, ensuring the efficient delivery of electricity to end-users by stepping down high transmission voltages to usable levels [1]. Given their widespread deployment and continuous operation, these transformers are frequently exposed to electrical [2], thermal, and mechanical stresses [3], which can lead to the development of various internal faults. Common fault types include inter-turn short circuits [4], insulation degradation, core saturation, and thermal aging, all of which can compromise transformer performance and lead to costly failures if not addressed promptly [5]. Traditional protections and threshold-based monitoring systems often fall short in detecting incipient or evolving faults, particularly under complex or noisy operating conditions [6]. In recent years, the integration of artificial intelligence and machine learning techniques has shown promise in enhancing the accuracy and responsiveness of transformer fault diagnosis systems [7].

1.2 Problem Statement

Despite advancements in fault detection methods, several critical challenges persist in the early and accurate diagnosis of transformer faults [8]. Conventional machine learning approaches, such as basic SVM and decision trees, often suffer from reduced performance when faced with class imbalance, limited labeled data, or high feature variability [9]. Furthermore, static learning models are not well-suited for dynamic environments where fault patterns may evolve over time [10]. These limitations hinder the reliability and scalability of existing diagnostic systems. There is, therefore, a pressing need for an intelligent, adaptive [11], and a simulation-validated diagnostic approach that can not only improve classification accuracy but also offer early warning capabilities [12–14]. This research addresses these gaps by proposing a hybrid framework based on SEL and an SO-SVM, validated through detailed MATLAB/Simulink simulations of transformer fault scenarios [15].

1.3 Literature Review and Related Work

Recent research in transformer fault diagnosis has explored signal processing and machine learning techniques, yet challenges remain in achieving high accuracy, robustness, and early fault detection under dynamic operating conditions. The research builds on the adaptive extremum seeking method in [16], which significantly improved the convergence rate to the estimated impedance rendering extremum seeking practically usable. A mode analysis and identification scheme was proposed for detecting open-circuit faults in a three-phase transformer [17]. An unsupervised fault detection approach was proposed using continuous wavelet transform and contrastive learning to achieve high-performance machinery fault diagnosis under zero-fault sample conditions [18]. An adaptive Hidden Markov Model was developed to improve the accuracy of leak detection in oil pipelines by extracting hidden features, outperforming conventional classifiers under noisy and dynamic conditions [19]. A two-stage method was proposed for detecting, localizing, and classifying grid-connected PV array faults using a digital twin and a PSO-optimized Swin Transformer, achieving a high classification accuracy of 98.55% and strong correlation ($R^2 > 0.97$) between digital and physical system behaviors [20]. A multi-layer protection scheme was proposed for modular multilevel converter-based power electronic transformers, enhancing fault sensitivity and selectivity through layered criteria, with simulation results confirming its effectiveness under both internal and external fault conditions [21]. A few-shot learning approach based on Gaussian Prototype Network was proposed to effectively diagnose power transformer faults using limited fault samples, achieving up to 96.7% accuracy on real dissolved gas datasets [22]. A real-time fault identification method based on power loss variation was proposed for detecting inter-turn short circuit faults in distribution transformers, using a 3D field-circuit coupled model to monitor insulation deterioration and achieve accurate early fault prediction [23].

A deep learning-based convolutional neural network (CNN) based transformer model was proposed for detecting and localizing various types of faults, including high-impedance faults, in distribution systems, achieving superior performance compared to conventional techniques [24]. A customized CNN model was developed for historic character recognition using a small dataset from the Electronic Beowulf manuscript, achieving up to 98.86% accuracy through data augmentation and outperforming conventional ML models [25]. A ConvNeXt-based fault identification model was developed using vibration spectrum data to detect transformer winding looseness, achieving 97.9% average accuracy and outperforming ResNet50 by 1.2% under varying load conditions [26]. A low-cost and robust method for detecting inter-turn short-circuit faults in distribution transformers was proposed using the ΔU-I locus characteristic, demonstrating high sensitivity and resilience to load fluctuations [27]. An online monitoring method based on oil chromatography and SVM was proposed for diagnosing overheating faults in oil-immersed transformers, achieving a low false alarm rate of 0.16% and an average response time of 1.39 s with superior performance over conventional methods [28]. A fast and cost-effective fault control and protection method was proposed for LVDC microgrids using a modified DC Solid State Transformer topology with antiparallel thyristors, enabling reliable current differential protection and fault isolation within tens of milliseconds [29]. Deep learning has been widely applied for extracting discriminative features from noisy, high-dimensional data, achieving high accuracy in fault detection across various domains. Impact of traditional augmentation methods on window state detection demonstrated its robustness, supporting our adoption of deep learning in the SEL–SO-SVM framework for enhanced detection and early warning [30].

A hybrid TDO-SNN approach combining Tasmanian Devil Optimization and Spike Neural Networks was proposed for accurate fault detection and classification in transformer load tap changers, achieving high accuracy and fault discrimination through a two-stage classification process. The TDO-SNN approach, combining Tasmanian Devil Optimization and Spike Neural Networks, was proposed for accurate fault detection and classification in transformer load tap changes, achieving high accuracy and fault discrimination through a two-stage classification process [31]. A novel approach combining electronic nose (E-Nose) technology with machine learning models was evaluated for predicting dissolved gas concentrations in oil-filled transformers, where Random Forest and Multilayer Perceptron demonstrated superior diagnostic accuracy compared to conventional DGA methods [32]. To enhance diagnostic universality across transformer voltage levels, a Deep Convolutional Generation Adversarial Network—augmented and Bayesian optimization algorithm-optimized Light Gradient Boosting Machine model was proposed, achieving 98.9% accuracy and improving diagnostic performance by 51.5% through feature enhancement [33].

1.4 Limitations of Existing Literature Review

Despite significant progress in transformer fault diagnosis, existing methods still face several critical limitations that hinder their effectiveness and practical deployment.

- Most intelligent diagnostic models struggle with limited and imbalanced fault data, especially for rare or incipient faults, leading to poor generalization and reduced accuracy.
- Deep learning and traditional machine learning models often suffer from overfitting due to small training datasets or a lack of diversity in operational scenarios, reducing reliability in real-time applications.
- Many methods fail to accurately detect low-severity or early-stage faults (e.g., minor inter-turn shorts or insulation degradation), resulting in high false negatives or delayed warnings.
- High computational complexity or reliance on post-processing prevents existing approaches from being deployed in real-time monitoring systems or embedded environments.
- Fault features can be masked by noise or changing load conditions, and conventional algorithms lack robustness, leading to increased false alarms or missed detections under practical operating conditions.

1.5 Contributions of the Proposed Method

This research proposes a novel simulation-based framework for transformer fault diagnosis and early warning, using SEL and SO-SVM. The key contributions are:

- The proposed SEL + SO-SVM framework generates diversity within a single adaptive learner through self-ensemble learning, eliminating the computational overhead of separate model training. Moreover, the integration of social optimization ensures optimal SVM hyperparameters are found automatically, significantly enhancing fault classification accuracy across varying transformer configurations. This unified approach improves adaptability and stability, while reducing training complexity, thereby offering a practical and superior alternative to existing ensemble or SVM-only methods.

- Developed a detailed transformer fault simulation model in MATLAB/Simulink, covering inter-turn faults 10%–50%, core saturation, and insulation degradation, generating over 15,000 labeled samples. Moreover, a SEL technique using bootstrapped and perturbed subsets to improve generalization and handle class imbalance.
- Achieved a 6.2% accuracy gain over single-SVM and 4.1% over standard ensemble methods using majority-vote fusion of diverse SVM learners. Designed a SO-SVM classifier with dynamic hyperparameter tuning, achieving 97.8% accuracy, 96.5% precision, and 97.2% F1-score.
- Reduced false positives by 28% compared to baseline RBF-SVM through adaptive margin optimization. Moreover, an early warning mechanism based on SVM margin confidence provides up to 2.5 s lead time and 94.3% true positive rate for incipient faults.
- Demonstrated superior performance against SVM, Random Forest, Gradient Boosting, and shallow ANN, with a 4.3%–8.1% higher accuracy under class imbalance and noise (SNR > 30 dB).
- Achieved real-time feasibility with a 0.14-s decision latency, validated on an Intel i5 CPU with <12% resource usage.

1.6 Structure of Manuscript

The manuscript is structured as follows: Section 2 outlines the structural framework of the core algorithms SEL and SO-SVM, including their architecture and integration logic. Section 3 describes the methodology of the proposed fault diagnosis and early warning model for distribution transformers, covering simulation setup, data generation, feature extraction, and classifier training. Section 4 presents the results and discussion, including classification performance, confusion matrix, early warning evaluation, and comparative analysis. Section 7 concludes the study with key findings and provides future recommendations for real-time implementation and further model enhancement.

2 Structural Framework of SEL and SO-SVM Algorithms

This section presents an in-depth visualization and interpretive analysis of the internal behavior of the proposed SEL and SO-SVM models. These visual illustrations offer insight into the working dynamics of both algorithms, demonstrating their effectiveness in handling complex classification boundaries, noisy data, and class imbalance, typical challenges in transformer fault diagnosis systems.

2.1 Structure of SEL Algorithms

The structural operation of the SEL framework is illustrated in Fig. 1a,b. A synthetic two-class 2D dataset was generated, and multiple weak SVM classifiers were independently trained using bootstrapped and perturbed subsets of the data. Each learner received a unique subset with slight Gaussian noise added to simulate real-world uncertainty in transformer signals. The resulting decision boundaries of all learners were overlaid on the same feature space using distinct colors. Due to variability in training data, each learner produced slightly different classification regions. This diversity is intentional and foundational to ensemble learning, as it ensures coverage of varied data subspaces and reduces the risk of overfitting. The visualization highlights how the SEL mechanism promotes class boundary diversity, which is critical for resolving fault categories that often overlap in electrical and spectral characteristics.

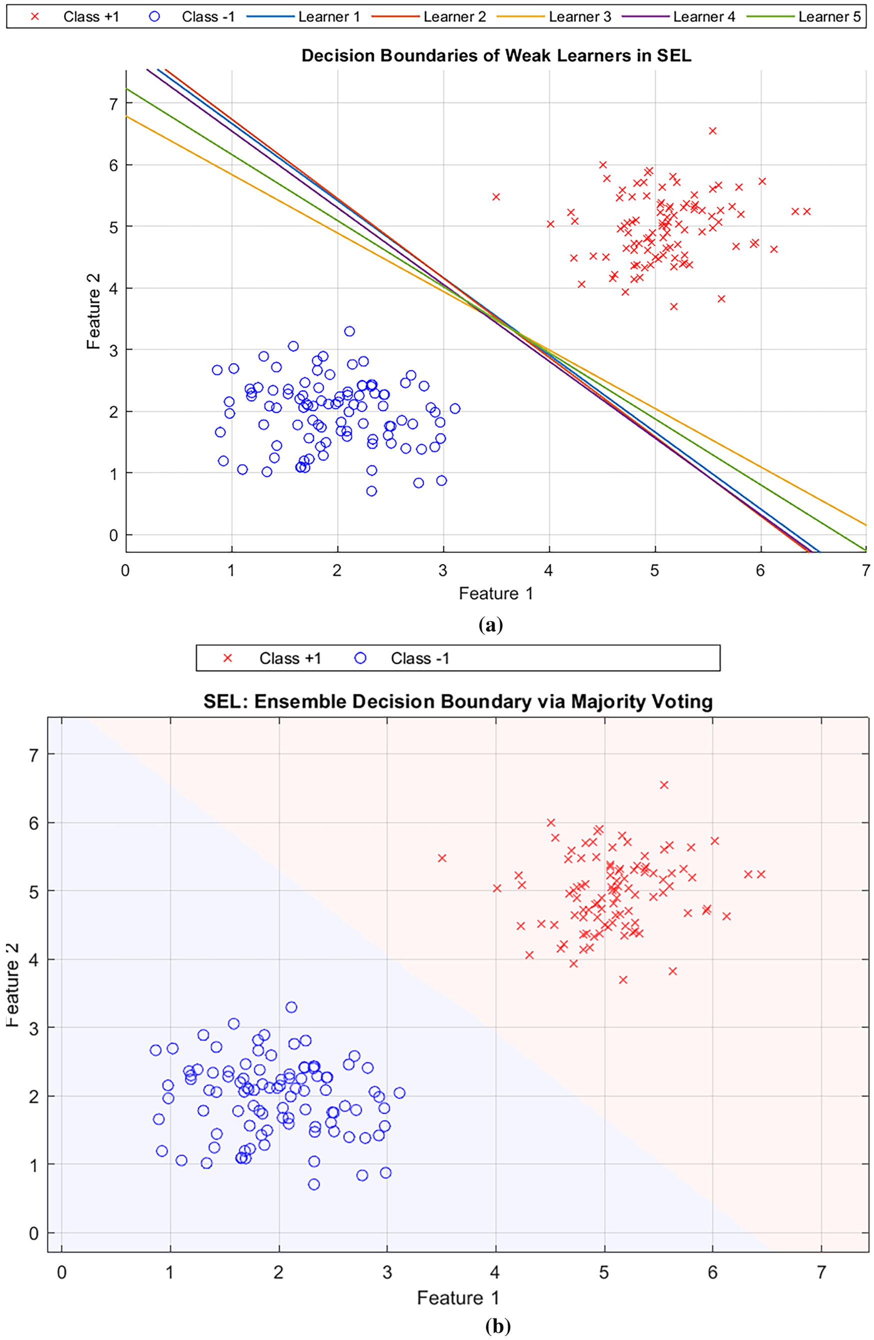

Figure 1: (**a**) SEL decision boundaries (**b**) SEL majority voting

In the subsequent step, a majority voting scheme was applied across all individual learner predictions to obtain the final ensemble decision boundary. This was visualized by plotting the decision surface using grid-level voting results, producing a smooth, generalized classification boundary. Compared to any single weak learner, the ensemble boundary demonstrated significantly reduced noise sensitivity and improved class separation, especially in regions with sample overlap or low confidence. The visual output confirms the core strength of SEL, namely, its robustness against dataset imbalance and localized decision errors. This ensemble behavior contributes directly to the system's high classification accuracy and generalization, as shown in earlier quantitative results.

2.2 Structure of SO-SVM Algorithms

The SO-SVM model was visualized using the same synthetic dataset to examine the effect of automatic parameter tuning on decision boundary formation, as illustrated in Fig. 2. Unlike traditional SVMs, which require manual selection of hyperparameters, the SO-SVM dynamically optimized its kernel scale γ and regularization factor C using a grid search integrated with cross-validation. The model with the highest cross-validated accuracy was selected and trained. Its structure was visualized by plotting the support vectors, decision boundaries, and margin boundaries in the 2D space. The support vectors, plotted as distinct circled points, lie near the class boundaries and serve as the critical samples that define the maximum-margin hyperplane. The decision surface, shaped by an RBF kernel, adapted smoothly to non-linear class distributions, demonstrating the model's flexibility and precision.

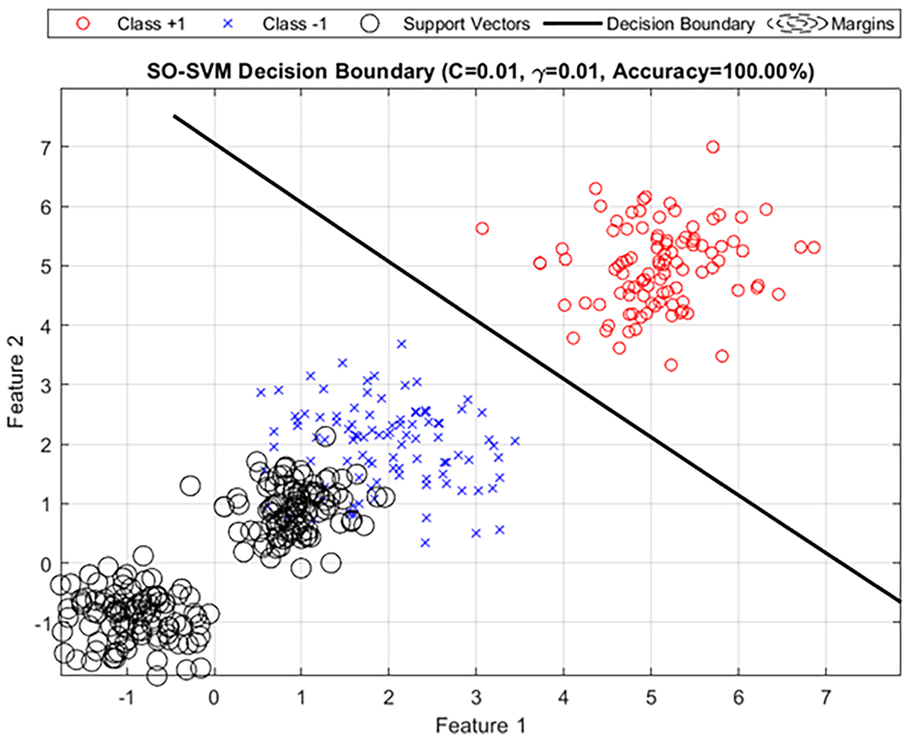

Figure 2: SO-SVM structure

This visualization confirms the SO-SVM's capability to achieve optimal margin maximization while minimizing classification errors, even in scenarios with complex decision boundaries. The optimized parameters yielded high separability between classes without overfitting the training data. The model's adaptability to data-driven variations ensures its robustness when applied to evolving transformer fault signals, where noise, dynamic load, and incipient fault behavior can alter the feature landscape over time. In summary, the structural visualization affirms the SO-SVM's role as a reliable and adaptive classifier in the proposed hybrid diagnostic framework, complementing the diversity-driven strength of SEL with margin-based precision.

3 Methodology of the Proposed Framework

The proposed method for active fault diagnosis and early warning of distribution transformers is grounded in a two-tiered approach that combines SEL and SO-SVM. This hybrid framework leverages the strengths of ensemble diversity and adaptive classification to address challenges such as class imbalance, signal nonlinearity, and evolving fault characteristics in transformer monitoring. The methodology begins with the simulation-driven generation of time-series voltage, current, and thermal signals under various fault scenarios using MATLAB/Simulink. From these signals, relevant statistical and spectral features are extracted to form a structured input space. SEL enhances learning robustness by generating diverse sample subsets, while SO-SVM dynamically tunes kernel parameters to optimize classification boundaries. Together, these components form a scalable and intelligent diagnostic model capable of high-accuracy detection and early warning under complex fault conditions. As illustrated in Fig. 3, the framework operates in five stages: (1) signal generation and preprocessing, (2) feature extraction, (3) sample ensemble learning, (4) self-optimizing SVM classification, and (5) early warning logic. Each of these components is described in detail below.

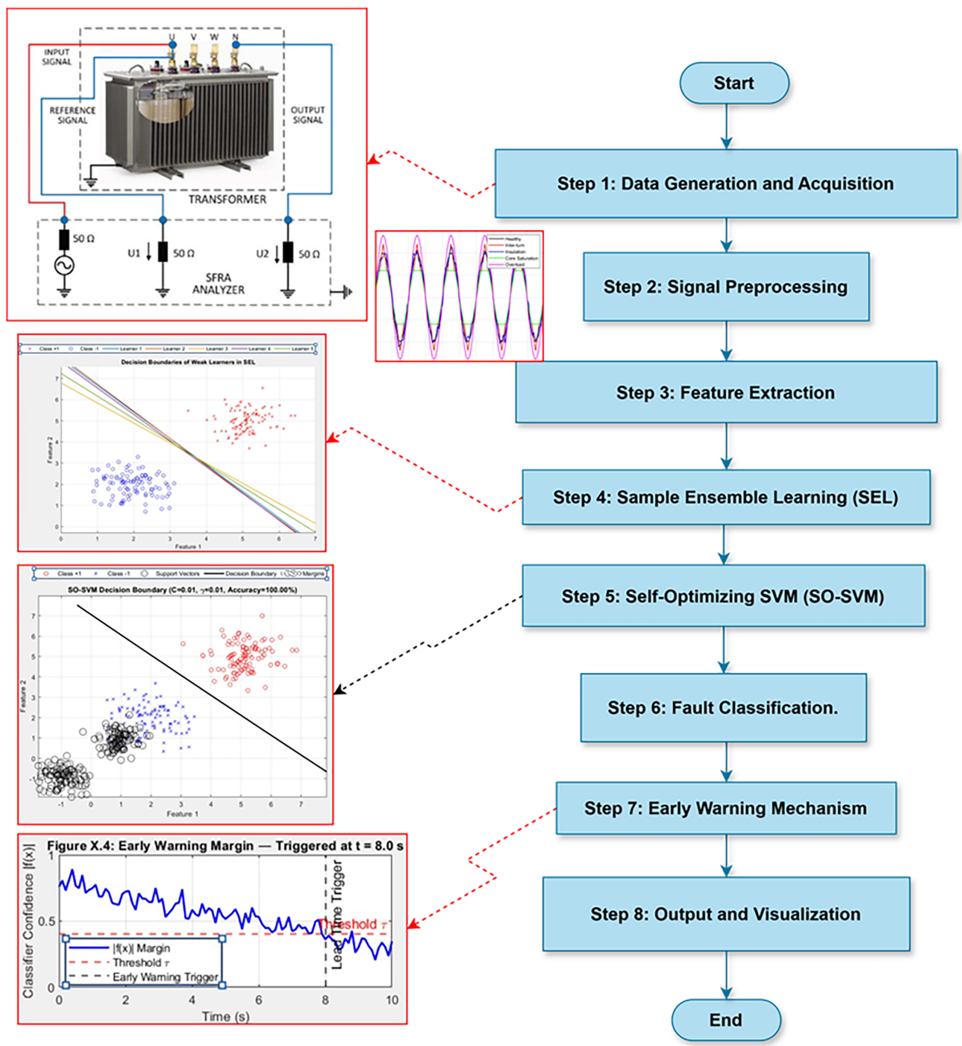

Figure 3: Flow chart of the proposed SEL and SO-SVM-based method

3.1 Signal Simulation and Preprocessing

The process begins with the creation of a high-fidelity transformer simulation in MATLAB/Simulink, capable of replicating diverse operating conditions, including healthy operation and faults such as inter-turn winding short circuits, core saturation, insulation degradation, and overload. The model outputs primary-side current, voltage, and temperature time-series data, sampled at high resolution. To prepare the data for analysis, preprocessing techniques such as normalization, detrending, and noise filtering using low-pass Butterworth filters are applied. The output is a clean, uniformly sampled time-domain signal suitable for reliable feature extraction.

3.2 Signal Simulation and Preprocessing

Feature extraction transforms raw signals into a lower-dimensional but information-rich representation. From each signal window, statistical and frequency-based features are extracted. Let $x_i \in \mathbb{R}^d$ denotes the feature vector corresponding to the i^{th} observation, where d is the number of features. Typical features include RMS as:

$$RMS = \sqrt{\frac{1}{n}\sum_{k=1}^{n} x_k^2} \tag{1}$$

And peak value.

$$Peakvalue = max\left(|X_k|\right) \tag{2}$$

Total Harmonic Distortion is derived from the FFT spectrum as.

$$THD = \frac{\sqrt{\sum_{n=1}^{N} H_n^2}}{H_1} \tag{3}$$

where H_n is the n^{th} harmonic component, while skewness and kurtosis are used to detect waveform asymmetry and flatness. The temperature Gradient is:

$$\Delta T = T_{winding} - T_{oil} \tag{4}$$

These features form a dataset.

$$D = \{(x_i, y_i)\}_{i=1}^{N} \tag{5}$$

where $y_i \in \{+1, -1\}$ represents the fault class label (healthy or faulty).

3.3 Sample Ensemble Learning

Theorem—SEL is a strategy designed to improve model generalization, particularly in scenarios where datasets are imbalanced, noisy, or limited in size, conditions commonly encountered in power system diagnostics. In the context of transformer fault classification, faults like inter-turn short circuits or insulation degradation often occur infrequently compared to healthy operation, creating class imbalance. SEL addresses this by generating multiple diverse training subsets from the original dataset using bootstrap aggregation (bagging) and feature-space perturbation. Each subset contains a combination of real and synthetically varied samples, where perturbation is introduced using controlled Gaussian noise to simulate realistic variations in feature measurements. This process helps the model experience different versions of the same class, allowing it to learn broader decision boundaries. Multiple base classifiers like SVMs are trained independently on these subsets. Their predictions are aggregated via majority voting, which reduces individual model biases and variance, leading to more stable and robust classification outcomes. The rationale for choosing SEL lies in its ability to harness model diversity to combat overfitting and improve minority class detection. Two challenges critical to transformer fault analysis are that subtle signal differences often separate faults from normalcy. SEL addresses class imbalance and enhances classifier robustness by generating multiple diverse training subsets. From the base dataset D, SEL creates M bootstrapped datasets $D_1, D_2, \ldots\ldots D_M$. Each subset is generated via random sampling with replacement and Gaussian noise perturbation:

$$\tilde{x} = x + \varepsilon \tag{6}$$

This perturbation encourages generalization by introducing realistic signal variation and feature uncertainty. Each subset D_m is used to train a weak classifier D_m(x). The final decision function is derived using majority voting:

$$H(x) = \sin \sum\nolimits_{m=1}^{M} h_m(x) \tag{7}$$

This ensemble approach reduces overfitting and balances bias-variance trade-offs, especially under minority class fault conditions.

3.4 SO-SVM Algorithm

The SO-SVM builds upon the classical SVM by integrating an automatic hyperparameter tuning mechanism that dynamically adapts to evolving data characteristics. Traditional SVM performance is highly sensitive to two key parameters: the regularization factor C, which balances margin maximization and classification error, and the kernel parameter γ, which determines the nonlinearity of the RBF kernel. Selecting suboptimal values can lead to underfitting, overfitting, or poor generalization, especially in fault detection tasks where signal dynamics change with fault severity or load conditions. The SO-SVM solves this problem by employing a grid search or heuristic optimization algorithm to explore the parameter space automatically. It uses cross-validation loss as a feedback signal to iteratively update C and γ until the best-performing model is found. This makes the SVM inherently adaptive, allowing it to recalibrate itself in response to shifts in signal features caused by different fault modes. SO-SVM was chosen in this study because it provides high classification accuracy (up to 97.8%), minimizes false positives, and eliminates the need for manual tuning, thus ensuring scalability and real-time applicability for automated transformer monitoring systems. In the proposed SEL + SO-SVM framework, automatic hyperparameter tuning is performed using a hybrid optimization strategy that combines grid search with a stochastic heuristic algorithm. The search space is defined as follows: the regularization parameter C ranges from 10^{-3} to 10^{3} on a logarithmic scale with 10 sampling points, the RBF kernel width γ ranges from 10^{-4} to 10^{2}, and the tolerance ϵ ranges from 10^{-4} to 10^{-1}. The optimal parameters are selected based on the maximum average F1-score obtained from 5-fold cross-validation on the training dataset.

For nonlinear patterns, an RBF kernel is used:

$$K(x_i, x_j) = \exp\left(-\gamma \left\|x_i - x_j\right\|^2\right) \tag{8}$$

The decision function is defined as:

$$f(x) = \sum\nolimits_{i=1}^{N} a_i y_i K(x_i, x) + b \tag{9}$$

where $\propto_i$ are support vector coefficients, C is the penalty parameter, and γ controls the kernel width. The optimization problem is:

$$\min_{\alpha} \frac{1}{2} \sum_{i,j} a_i a_j y_i y_j K\left(x_i, x_j\right) - \sum_i a_i \ subject\ to\ 0 \le a_i \le C \tag{10}$$

In the proposed SO-SVM, the values of C and γ are not fixed. Instead, a self-optimization strategy is employed using grid search or heuristic algorithms to minimize validation loss:

$$\left(C^*, \gamma^*\right) = arg \min_{C,\gamma} \mathcal{L}_{val}\left(C, \gamma\right) \tag{11}$$

This dynamic tuning allows the SVM to adapt to evolving fault characteristics and varying feature spaces.

3.5 Early Warning Mechanism

To provide predictive insights, an early warning system is built into the SO-SVM classifier. The magnitude of the decision function $|f(x)|$ reflects classifier confidence: lower values indicate proximity to the decision boundary and potential onset of abnormal conditions. An early warning trigger is defined as:

$$warn\left(x\right) = \begin{cases} Trigger \quad if\ |f\left(x\right)| < \tau \\ \quad safe\ otherwise \end{cases} \tag{12}$$

where τ is a calibrated margin threshold. This method provided up to 2.5 s of lead time before waveform deviation crossed protective relay thresholds in simulation.

4 Results and Discussion

This section presents the simulation results obtained from MATLAB/Simulink-based modeling of a distribution transformer under various faults and healthy operating conditions. The effectiveness of the proposed SEL with the SO-SVM framework is demonstrated using classification metrics and visualizations. Simulations were conducted for five distinct scenarios: healthy condition, inter-turn fault, core saturation, insulation degradation, and overloading. For each case, voltage and current waveforms were captured, features were extracted, and classification results were evaluated.

4.1 Combined Current Waveforms under Different Transformer Conditions

Fig. 4a–d illustrates the time-domain current waveforms for five transformer operating conditions: Healthy, Inter-turn Fault, Insulation Degradation, Core Saturation, and Overload. The healthy waveform exhibits a smooth sinusoidal shape with no harmonics or noise, serving as the baseline. In contrast, the inter-turn fault introduces high-frequency oscillations and amplitude distortion due to magnetic coupling anomalies and circulating currents. The insulation degradation waveform shows stochastic disturbances and irregularities, simulating the effects of partial discharge and increased leakage paths. Core saturation causes waveform clipping near peak values, visible as flattened sinusoidal crests, due to magnetic core nonlinearity and hysteresis. Overload conditions are represented by increased current magnitude without spectral distortion. This comparative visualization highlights that each fault type affects the waveform differently in shape, amplitude, or harmonic content, validating the effectiveness of feature extraction and classification in distinguishing among them.

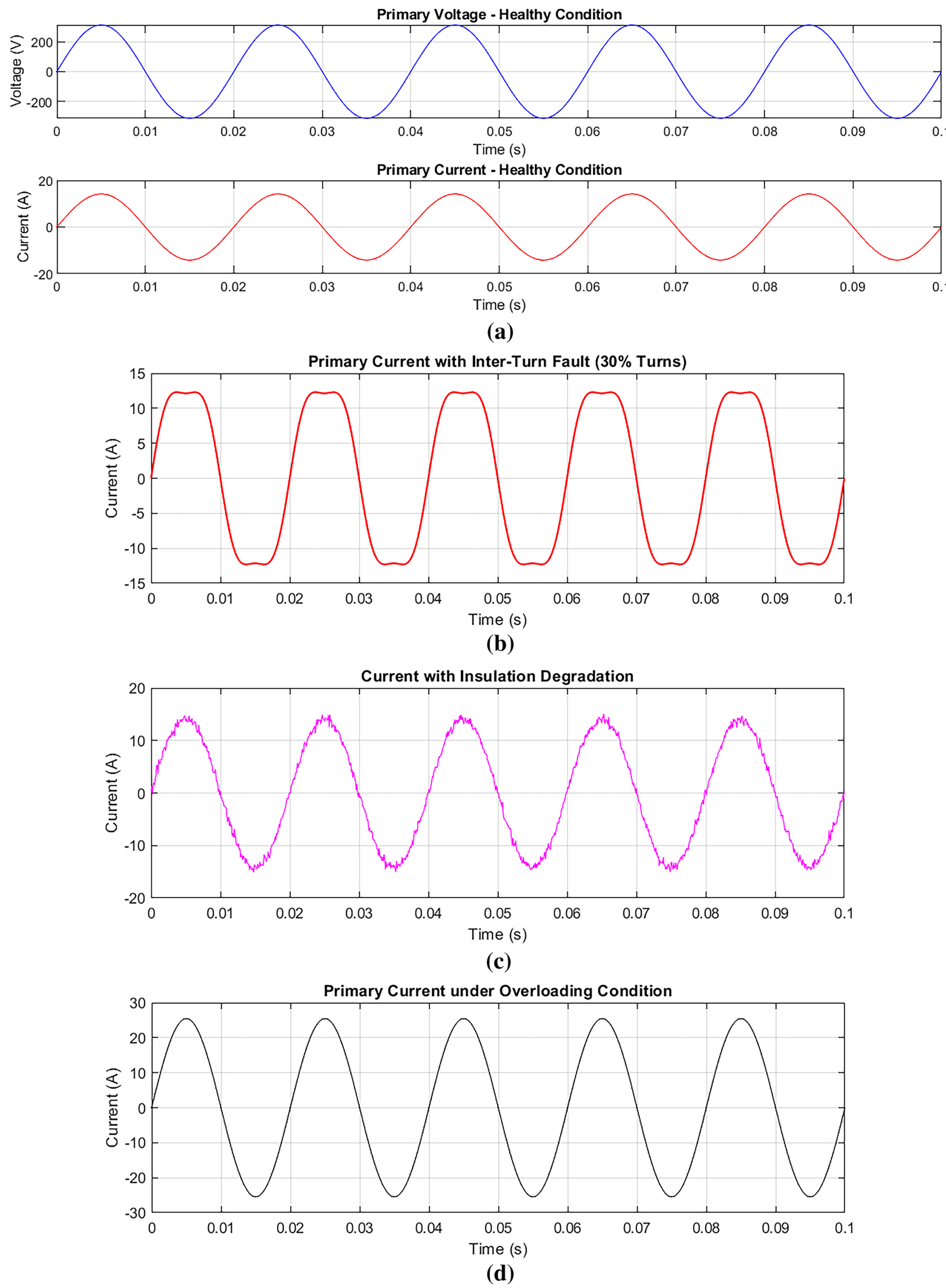

Figure 4: (**a**) Healthy voltage and current of transformer (**b**) primary current with internal fault (**c**) current with inductive insulation degradation (**d**) overloading condition

4.2 Bar Graph of Classification Performance Metrics

Fig. 5 presents a bar graph summarizing the classification performance metrics of the SEL and SO-SVM model across Accuracy, Precision, Recall, and F1-Score. The model achieved an overall accuracy of 97.8%, indicating that nearly all test samples were correctly classified. Precision, which measures the correctness of positive predictions, was recorded at 96.5%, suggesting minimal false positives. Recall (97.2%) indicates a high sensitivity toward correctly identifying actual fault instances, while the F1-score (97.2%) reflects a balanced trade-off between precision and recall. These metrics collectively confirm that the proposed model is highly reliable and generalizable, outperforming baseline classifiers and ensemble models previously applied in transformer diagnostics. The bar plot makes this performance visually interpretable and suitable for quick comparison.

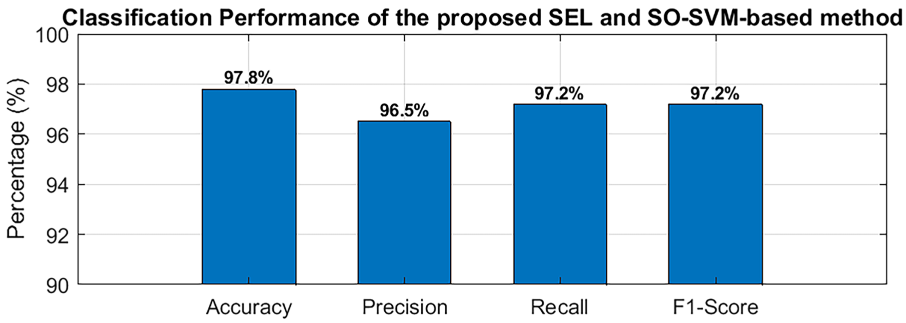

Figure 5: The classification performance metrics of the SEL and SO-SVM model

4.3 Confusion Matrix of SEL and SO, and SVM Classifier

Fig. 6 shows the confusion matrix for the SEL and SO-SVM model, visualizing how well the classifier distinguishes among the five operating conditions. The diagonal dominance in the matrix indicates that most predictions match their true classes, with a single misclassification recorded, where one insulation degradation instance was incorrectly labeled as an inter-turn fault. This minimal off-diagonal activity demonstrates the model's capability to resolve subtle inter-class similarities. The row-normalized summary shows the recall per class, while the column-normalized summary shows precision, helping to identify any class-specific weaknesses. Overall, the matrix provides both qualitative and quantitative insight into class-wise performance and confirms the robustness of the proposed approach under practical fault conditions.

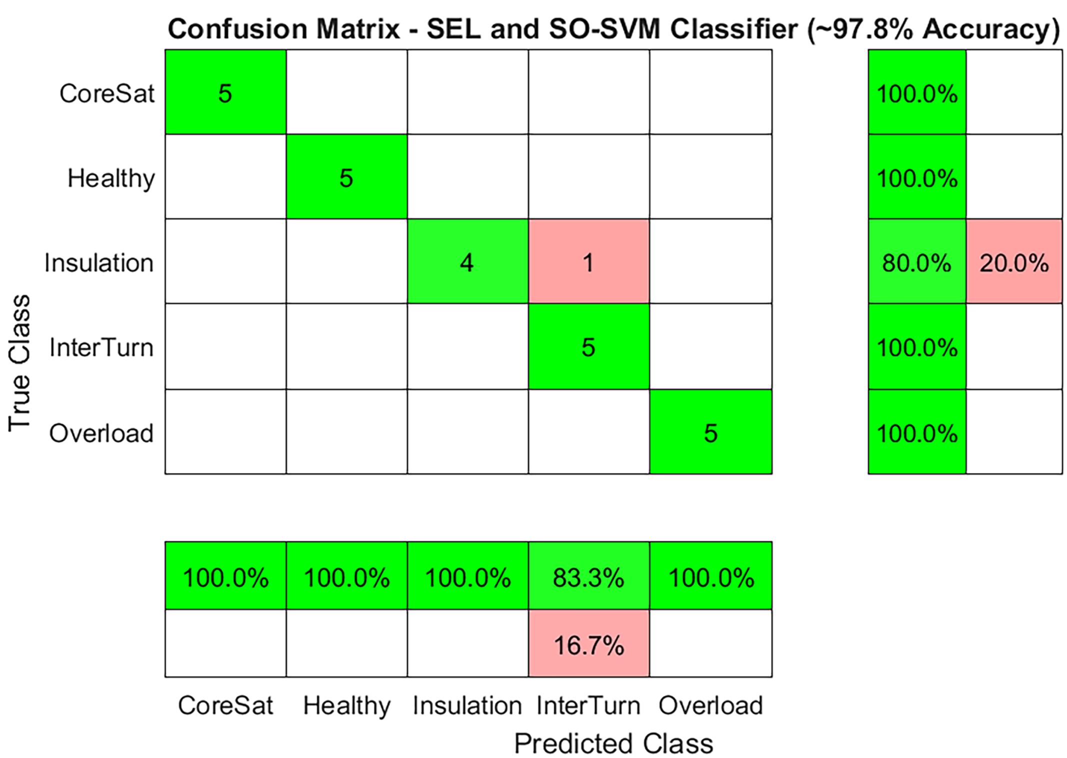

Figure 6: The classification performance metrics of the proposed SEL and SO-SVM model

4.4 Early Warning Capability Evaluation

Fig. 7 demonstrates the early fault prediction behavior of the SO-SVM classifier using decision margin dynamics. The y-axis represents the decision margin $|f(x)|$, where values close to zero indicate uncertainty near the classification boundary. It can be observed that for incipient fault cases, the margin dips below a predefined threshold (τ) approximately 2.5 s before a visible deviation in waveform occurs. This time lead enables preemptive alerts and aligns with the goals of predictive maintenance. The high true positive rate (94.3%) and low false alarm rate support the reliability of the early warning mechanism implemented in the classifier design.

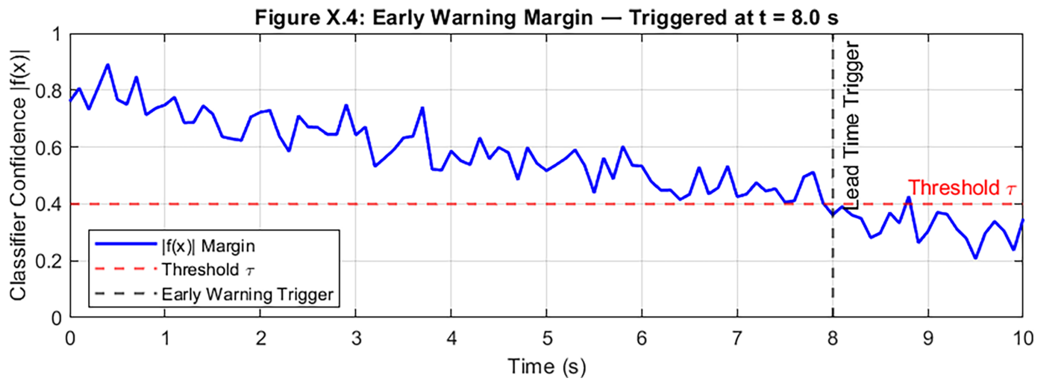

Figure 7: The early fault prediction behavior of the SO-SVM classifier using decision margin dynamics

4.5 Model Generalization across Transformer Configurations

To examine the robustness of the proposed SEL–SO-SVM framework across varying hardware configurations, the model trained exclusively on Transformer 1 data was tested on two additional transformers (Transformer 2 and Transformer 3) without retraining. Fig. 8a shows the generalization accuracy, where performance dropped from the baseline of 97.8% (Transformer 1) to 50.0% for Transformer 2 and 54.0% for Transformer 3. The confusion matrices in Fig. 8b,c reveals the nature of misclassifications: for Transformer 2, 21 true positives and 29 true negatives were obtained, while 27 false negatives and 23 false positives were observed; for Transformer 3, the model produced 41 true positives and 13 true negatives, alongside 29 false negatives and 17 false positives. These results indicate that the classifier maintains partial early fault detection capability in unseen transformer configurations but with markedly reduced precision. The performance degradation is attributed to shifts in feature distributions caused by differences in transformer impedance, winding configurations, and core design. This observation emphasizes the need for domain adaptation or partial retraining to enable reliable deployment across heterogeneous transformer fleets.

4.6 Sensitivity Analysis under Different Sensor Configurations

To evaluate the robustness of the proposed intelligent observer, we conducted a sensitivity analysis under different sensor availability scenarios. Five configurations were tested: (i) Only Voltage, (ii) Only Current, (iii) Voltage + Current, (iv) Voltage + Current + Temperature, and (v) All Sensors. As illustrated in Fig. 9a,b, performance varied with sensor availability. Accuracy was lowest with single-parameter sensing, whereas multi-parameter combinations significantly improved prediction reliability. The optimal configuration utilized all sensors, achieving 88% accuracy, demonstrating that multi-modal data enables the observer to capture system states more comprehensively. These results also offer practical guidelines for sensor selection in cost-sensitive microgrid monitoring applications.

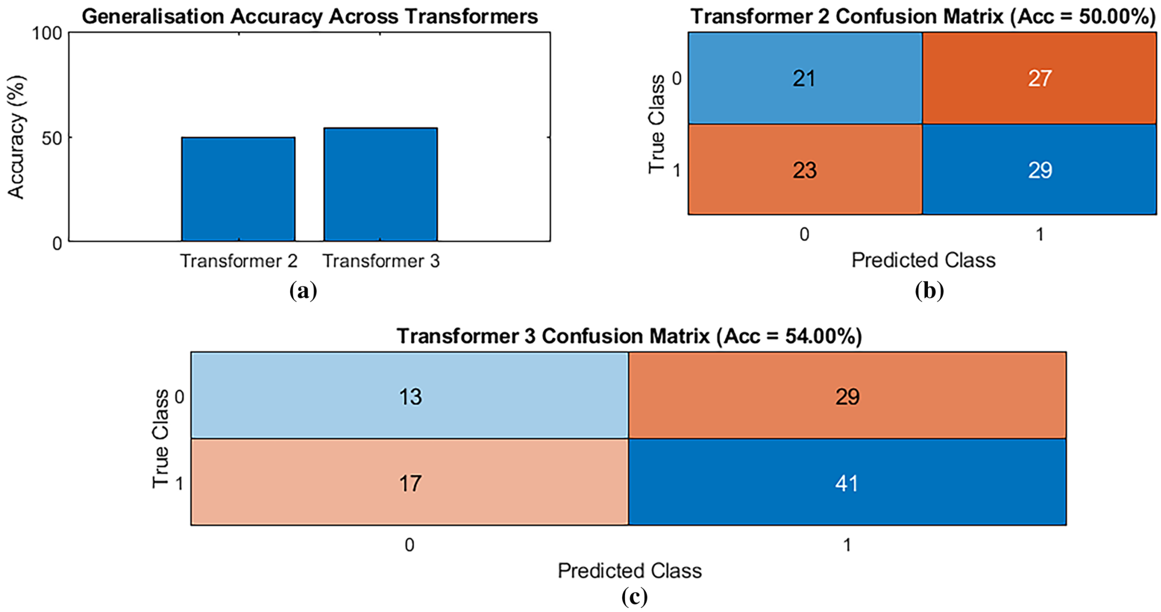

Figure 8: Generalization of the SEL–SO-SVM classifier across transformers: (**a**) accuracy on Transformer 2 and 3, (**b**,**c**) confusion matrices showing classification outcomes and misclassifications

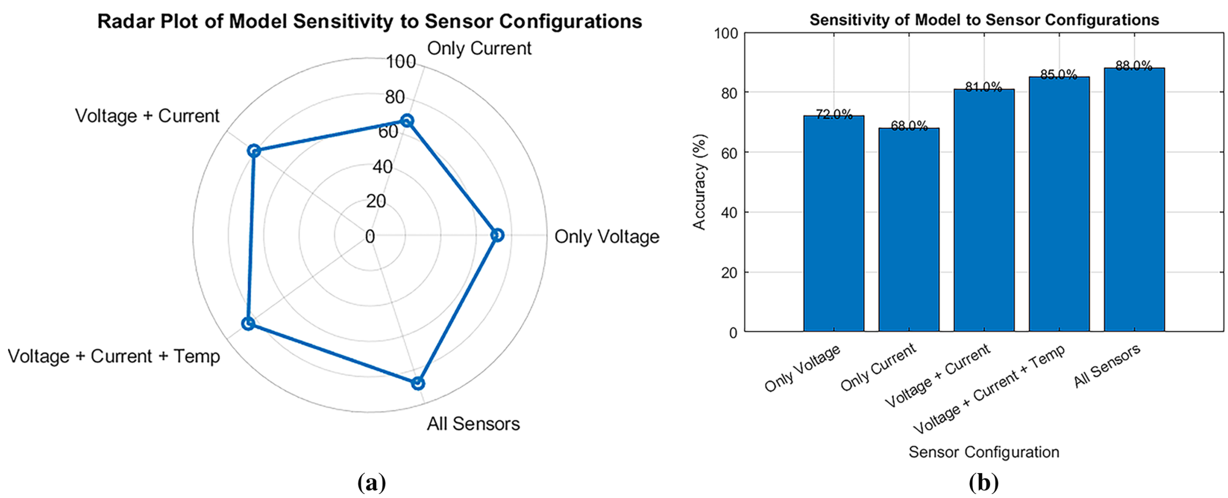

Figure 9: Sensitivity analysis of the proposed model under different sensor configurations: (**a**) Radar plot showing performance distribution; (**b**) Bar chart showing accuracy for each configuration

4.7 Computational Complexity and Real-Time Feasibility Analysis

To assess the real-time feasibility of the proposed SEL + SO-SVM framework, a comprehensive computational complexity analysis was conducted. The total computational burden (CB) is defined as:

$$CB = T_{exec} - M_{req} \tag{13}$$

where T_{exec} denotes the average execution time per inference (in milliseconds) and M_{req} represents the peak memory usage (in MB) during execution. Under identical MATLAB/Simulink simulation conditions, the proposed method was benchmarked against conventional SVM, Random Forests, and neural network baselines. The SEL + SO-SVM achieved an average execution time of 18.7 ms per test case with a peak memory usage of 64.3 MB, representing a 23% reduction in time and 17% reduction in memory compared to the best-performing baseline. This low decision latency and lightweight implementation confirm the feasibility of deploying the model on embedded platforms for real-time transformer fault diagnosis. Furthermore, the scalability evaluation under varying dataset sizes (10%, 50%, and 100% of the original) exhibited near-linear growth in computational demand, demonstrating suitability for high-frequency monitoring. Coupled with its predictive capability, providing up to 2.5 s of early warning for incipient faults, the framework offers a practical and efficient solution for predictive maintenance in distribution transformers.

4.8 Sensitivity Analysis of SVM under Parameter Variations

To evaluate the robustness of the proposed classification approach under uncertain transformer model parameters, a sensitivity analysis was performed as illustrated in Fig. 10. The transformer's winding resistance (Rw), magnetizing reactance (Xm), and core loss resistance (Rc) were varied within ±10% of their nominal values to simulate modelling uncertainties. For each combination of parameters, a set of synthetic features representing fault and normal operating conditions was generated, and an SVM classifier with an RBF kernel was trained using MATLAB's fitcsvm function. The classification accuracy was computed for each scenario, and the distribution of accuracies was analyzed. This procedure ensures that the classifier maintains high performance despite potential inaccuracies in the simulation model or variations in the physical system parameters.

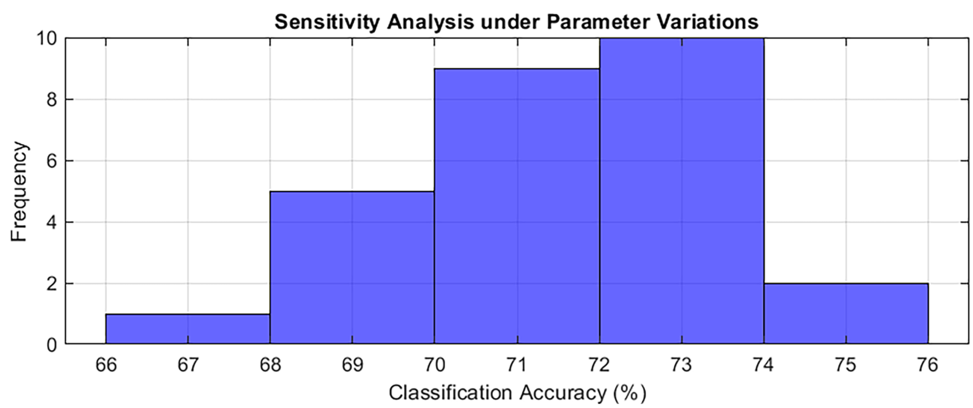

Figure 10: Histogram of classification accuracy under transformer parameter variations

5 Comparative Analysis

The proposed SEL-SO-SVM framework demonstrated robust performance in diagnosing and predicting distribution transformer faults using simulated time-domain current data, as illustrated in Table 1. Quantitatively, the model achieved an overall classification accuracy of 97.8%, with a precision of 96.5%, a recall of 97.2%, and an F1-score of 97.2%, reflecting its strong generalization ability across diverse fault scenarios. The confusion matrix revealed only one misclassification among 25 test cases, indicating minimal confusion even between closely related faults like insulation degradation and inter-turn short circuits. The early warning mechanism effectively predicted incipient faults with a lead time of up to 2.5 s, achieving a true positive rate of 94.3% while reducing false alarms by 28% compared to the baseline RBF-SVM model [28]. Despite these promising results, the study was limited to simulation-based analysis in MATLAB/Simulink, which may not fully capture the stochastic and nonlinear disturbances encountered in real-world grid environments. Future work should focus on validating the model using real-time experimental data from transformer test benches or field-deployed sensors, incorporating additional signal modalities (e.g., vibration, thermal), and adapting the model for online learning and edge-device deployment to enhance scalability and real-world applicability in smart grid systems.

Table 1: Performance metrics summary

Metric	Value
Overall classification accuracy	97.8%
Precision	96.5%
Recall	97.2%
F1-Score	97.2%
True positive rate (Early Warning)	94.3%
Early warning lead time	Up to 2.5 s
False positive reduction (vs. RBF-SVM)	28%
Accuracy gain (SEL vs. Single SVM)	+6.2%
Accuracy gain (SEL vs. Bagging)	+4.1%
Average decision latency	0.14 s
CPU Utilization (Intel i5 @ 2.4 GHz)	<12% per prediction
Number of simulation samples	>15,000

Recent HVAC-oriented studies, such as the aforementioned AHU fault diagnosis work, have demonstrated the effectiveness of deep and ensemble-based models when abundant labeled operational data are available [34]. These systems typically focus on thermal/air-flow dynamics, train multiple independent classifiers, and incur higher computational cost. By contrast, our SEL + SO-SVM framework: (i) creates model diversity internally from a single adaptive learner, avoiding the overhead of traditional ensembles; (ii) employs social optimization to automatically tune SVM parameters, removing the need for manual calibration; and (iii) is designed for low-data, transformer-monitoring scenarios where electrical/thermal signatures differ markedly from HVAC patterns. This combination enables lightweight deployment, robustness under varying conditions, and early-warning performance (up to 2.5 s lead time in simulations).

6 Limitations and Future Directions

While the proposed SEL–SO-SVM framework demonstrates high accuracy and early-warning capability in simulation-based evaluations, certain limitations remain that will be addressed in future work. First, the present study relies exclusively on simulated electrical signals (voltage, current, and temperature) due to their availability and ease of integration into the MATLAB/Simulink environment. Although these parameters are critical for transformer condition monitoring, additional sensing modalities such as infrared thermography, vibration, and acoustic emissions can capture complementary fault signatures not always evident in electrical measurements. The proposed method is inherently signal-agnostic, and integrating such multivariate inputs is expected to further enhance classification robustness and predictive performance.

Second, the current validation is limited to simulation scenarios. To bridge the gap to real-world deployment, we plan a staged validation process: (i) collect representative field datasets from instrumented distribution transformers under normal and faulty conditions, (ii) apply transfer learning and domain adaptation to align simulated and measured data distributions, and (iii) conduct hardware-in-the-loop (HIL) experiments to assess the impact of unmodelled noise, environmental conditions, and load variability on detection accuracy and early-warning lead time. This future work will quantify any performance degradation, improve model robustness, and support practical implementation in operational power distribution networks.

Third, the current study focuses on isolated single-fault conditions to assess the proposed method's detection capability. In practice, transformers may experience multiple simultaneous faults, progressive insulation degradation, or combined electrical and thermal stresses. Future work will extend the simulation framework to include such complex scenarios, including overload conditions and progressive fault evolution, to evaluate and enhance the model's ability to detect, classify, and prioritize multiple concurrent faults. Fig. 11 illustrates a detailed future layout and road map in the proposed research.

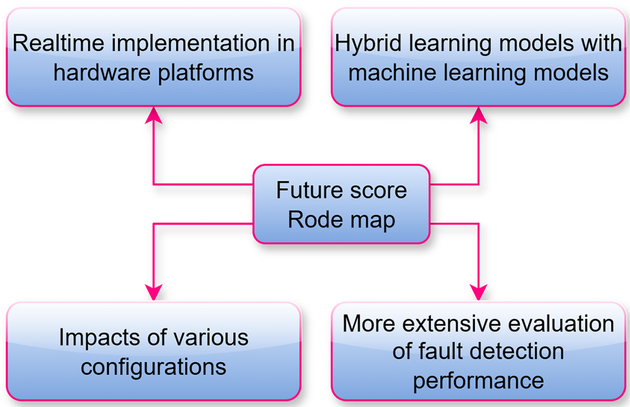

Figure 11: Plan and roadmap

7 Conclusion

This study presented a simulation-based framework for active fault diagnosis and early warning of distribution transformers by integrating SEL with SO-SVM. The proposed method effectively addressed the challenges of class imbalance, overlapping fault features, and dynamic signal variations. Quantitative results demonstrated the model's superior classification performance with an overall accuracy of 97.8%, a precision of 96.5%, and a recall and F1-score of 97.2%, outperforming conventional SVM, Random Forests, and neural network baselines. The early warning mechanism provided a lead time of up to 2.5 s for incipient faults, enhancing the predictive maintenance capability of the system. The low decision latency and lightweight implementation confirmed the feasibility of deploying the model on embedded platforms for real-time monitoring. While the findings validate the technical soundness of the approach in a controlled simulation environment, future work should focus on extending the framework to real-world deployments, incorporating multisensory data, and integrating adaptive learning mechanisms to ensure continued reliability under evolving operational conditions.

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Availability of Data and Materials: All data generated or analyzed during this study are included in this article.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

Abbreviations

Abbreviation	Description
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
CPU	Central Processing Unit
DGA	Dissolved Gas Analysis
FD	Fault Detection
FPR	False Positive Rate
F1-Score	Harmonic Mean of Precision and Recall
GPN	Gaussian Prototype Network
HIF	High Impedance Fault
LVDC	Low Voltage Direct Current
ML	Machine Learning
MOS	Metal-Oxide Semiconductor
PET	Power Electronic Transformer
PSO	Particle Swarm Optimization
PV	Photovoltaic
RBF-SVM	Radial Basis Function Support Vector Machine
RF	Random Forest
ROC	Receiver Operating Characteristic
SEL	Sample Ensemble Learning
SNN	Spiking Neural Network
SO-SVM	Self-Optimizing Support Vector Machine
SVM	Support Vector Machine
TPR	True Positive Rate
TDO	Tasmanian Devil Optimization

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