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Enhancing Transformer Protection: A Machine Learning Framework for Early Fault Detection

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Abstract: The reliable operation of power transformers is essential for grid stability, yet existing fault detection methods often suffer from inaccuracies and high false alarm rates. This study introduces a machine learning framework leveraging voltage signals for early fault detection. Simulating diverse fault conditions—including single line-to-ground, line-to-line, turn-to-ground, and turn-to-turn faults—on a laboratory-scale three-phase transformer, we evaluated decision trees, support vector machines, and logistic regression models on a dataset of 6000 samples. Decision trees emerged as the most effective, achieving 99.90% accuracy during 5-fold cross-validation and 95% accuracy on a separate test set of 400 unseen samples. Notably, the framework achieved a low false alarm rate of 0.47% on a separate 6000-sample healthy condition dataset. These results highlight the proposed method's potential to provide a cost-effective, robust, and scalable solution for enhancing transformer fault detection and advancing grid reliability. This demonstrates the efficacy of voltage-based machine learning for transformer diagnostics, offering a practical and resource-efficient alternative to traditional methods.

Keywords: power transformer; fault detection; machine learning; decision trees; voltage analysis; classification algorithms

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1. Introduction

Transformer failures in electrical power systems can lead to costly outages, significant equipment damage, and compromised grid stability. Timely and accurate fault detection is essential to prevent these failures. Traditional methods like dissolved gas analysis (DGA) and frequency response analysis (FRA) have been widely used but face limitations in real-world applications [1–4]. These techniques can be time-consuming, require specialized equipment, and lack precision in detecting early-stage faults. Moreover, they rely on expert interpretation and predefined thresholds, increasing the risk of misdiagnosis or delayed responses. This underscores the need for more efficient and reliable fault detection methods.

Machine learning (ML) offers a promising, data-driven alternative for transformer fault diagnosis [5]. However, current ML approaches are often limited by their reliance on manually selected features and simplistic models, which struggle to capture the complex behavior of transformer faults. Furthermore, these models are less effective when dealing with imbalanced datasets—a common issue in fault detection where normal operating conditions significantly outnumber fault instances—resulting in poor detection rates for rare but critical internal faults. This highlights the necessity for a more advanced and adaptive solution.

In this study, the authors aim to develop a machine learning-based approach for enhancing transformer fault detection using readily available voltage signals. The authors assess the performance of three models—decision trees, support vector machines (SVMs), and logistic regression—in diagnosing fault types such as single line-to-ground, line-to-line, turn-to-ground, and turn-to-turn faults.

Logistic regression, a widely used statistical method for binary classification, is an essential baseline for distinguishing between healthy and faulty transformer conditions [6,7]. This model predicts the probability of a categorical outcome by employing a logistic (sigmoid) function, which maps a linear combination of input features to a probability value between 0 and 1. A classification threshold (commonly set to 0.5) determines the predicted class, making logistic regression an intuitive yet effective tool for fault detection. In the context of transformer diagnostics, it leverages voltage signals to identify potential faults and classify the transformer's health status [8,9]. The implementation, conducted in MATLAB using the fitglm function, highlights logistic regression's practical role in this study (further details in Section 2.5).

Comprehensive data acquisition strategies are employed to ensure accurate voltage measurements, and model performance is rigorously evaluated using k-fold cross-validation and metrics such as accuracy, precision, recall, and in F4561-score. To address imbalanced datasets and limited real-world data, the authors incorporate advanced data-balancing techniques and explore cost-effective solutions. Ultimately, this research aims to create more robust and reliable fault diagnosis systems, improving the stability and resilience of electrical grids.

1.1. Literature Review

Power transformers are crucial in maintaining the stability and reliability of electrical power grids. Accurate and timely fault detection prevents costly outages and equipment damage. While traditional diagnostic techniques such as dissolved gas analysis (DGA) and frequency response analysis (FRA) have been widely used, they face limitations in speed and scalability. Machine learning (ML) has emerged as a promising solution, enhancing fault detection capabilities. However, the 'black box' nature of many ML algorithms presents challenges for interpretability, a critical requirement in high-stakes applications. This review focuses on interpretable ML models, including decision trees, support vector machines (SVMs), random forests, and gradient boosting, examining their performance, computational efficiency, and suitability for transformer fault detection. This emphasis on interpretability ensures that fault diagnoses are transparent, supports regulatory compliance, and facilitates maintenance.

1.1.1. Interpretable Machine Learning Models

Decision Trees

Decision trees are highly interpretable due to their straightforward hierarchical structure. Each decision point can be visualized, making it easy to trace how a fault diagnosis is made [10,11]. This clarity makes them valuable for early warning systems in transformer operations. However, decision trees are prone to overfitting, especially with complex datasets, potentially leading to a higher rate of false negatives in detecting subtle faults [12].

Support Vector Machines (SVMs)

SVMs are powerful in distinguishing between internal faults and external disturbances. They excel in noisy environments and can effectively separate fault types with complex boundaries [13,14]. While not as naturally interpretable as decision trees, examining support vectors can provide insight into decision-making. SVMs typically offer high accuracy in complex fault scenarios, making them valuable for distinguishing subtle fault characteristics, though they are computationally expensive.

Random Forests

Random forests mitigate overfitting by aggregating predictions from multiple decision trees, resulting in more robust models. Feature importance scores can be extracted, highlighting the most influential variables in fault detection [15,16]. This enhances interpretability and helps operators understand the drivers behind fault diagnoses. However, random forests require moderate computational resources, which can limit their use in real-time systems.

Gradient Boosting

Gradient boosting models deliver high accuracy and firm performance in fault detection, especially when handling complex and overlapping data patterns [14]. While inherently less interpretable, techniques such as SHAP (Shapley additive explanations) values can quantify feature contributions to individual predictions, offering more profound insights into the model's decision-making process [17]. However, gradient boosting's computational complexity can be a barrier to real-time application, necessitating efficient implementations for practical deployment.

1.1.2. Interpretable Machine Learning Models

Table 1 summarizes the discussed models, highlighting the tradeoffs between interpretability, computational efficiency, and performance.

Table 1. Comparison of machine learning models for transformer fault detection.

Model	Interpretability	Computational Efficiency	Performance (Accuracy)	Key Strengths	Ref.
Decision Tree	High	High	Moderate	Simple, easy to visualize, fast training	[10–12,18]
Random Forest	Moderate	Moderate	High	Robust, handles high dimensionality well	[12,15–17,19]
Gradient Boosting	Moderate	Low	Very High	Excellent predictive accuracy, robust feature analysis	[12,16,17]
SVM	Moderate	Moderate	High	Effective at complex boundary separation	[13,14,18,20,21]

This comparative analysis highlights the tradeoffs between interpretability, computational efficiency, and accuracy for each model type. Decision trees offer the highest interpretability but may struggle with complex problems. Random forests and gradient boosting provide excellent performance at the cost of some interpretability and computational efficiency. SVMs balance performance and efficiency but can be challenging to interpret, especially in high-dimensional spaces.

1.1.3. Performance and Computational Efficiency

Balancing high performance with computational efficiency is critical for real-time fault detection. Hybrid approaches, integrating ML with traditional techniques like DGA and FRA, offer a promising solution [20,22]. ML models can provide rapid initial screenings for faults, which are then validated by traditional methods. This combination leverages the speed of ML and the accuracy of established techniques. Additionally, deploying ML models on specialized hardware, such as FPGAs (field-programmable gate arrays) [21], can improve inference times, making real-time fault detection feasible in high-demand systems.

1.1.4. Data and Feature Engineering

Practical feature engineering is pivotal for enhancing both performance and interpretability in ML models. Extracting meaningful features from raw data, such as current, voltage, and vibration signals, is essential for accurate fault detection. Time-domain features (e.g., RMS values, peak values) and frequency-domain features (e.g., harmonic components) help capture fault characteristics. In contrast, time–frequency features derived from wavelet transforms capture transient fault signatures crucial for detecting incipient faults.

Feature selection techniques like principal component analysis (PCA) and recursive feature elimination (RFE) help reduce dimensionality, enhancing model interpretability while maintaining performance.

1.1.5. Addressing Class Imbalance

Transformer fault detection datasets are typically imbalanced, with fewer fault instances than normal operations. This imbalance can bias ML models toward predicting the majority class, leading to poor fault detection rates. SMOTE (synthetic minority oversampling technique) and ADASYN (adaptive synthetic sampling approach) effectively generate synthetic fault samples to balance the dataset. Cost-sensitive learning, which assigns higher misclassification penalties to minority classes, can also improve fault detection accuracy without distorting the dataset [23].

1.1.6. Challenges and Future Directions

Despite advancements in machine learning for transformer fault diagnosis, several challenges remain, hindering widespread adoption and optimal performance:

1. *Data Quality and Availability*: Access to diverse, high-quality, real-world datasets is essential for training robust, generalizable models. Many studies' reliance on synthetic data limits the models' applicability to real-world conditions, where data are often scarce, imbalanced (with healthy conditions outnumbering faults) [24–26], and noisy (particularly voltage signals) [27–30]. This study addresses this challenge by using readily available voltage signals and employing preprocessing techniques like outlier removal and noise filtering [31,32] to improve data quality and reliability. Furthermore, we utilize decision trees, known for their resilience to imbalanced data [33,34], and rigorous evaluation methods like k-fold cross-validation to ensure generalizability even with limited real-world data [35,36].
2. *Real-time Processing*: Optimizing ML models for instantaneous decision-making in critical power systems requires further research. Deploying models on specialized hardware and developing more efficient algorithms are key to achieving this goal.
3. *Model Interpretability vs. Performance*: Achieving high accuracy while maintaining interpretability remains challenging, particularly for complex models like gradient boosting and SVMs. Future research should focus on improving interpretability without sacrificing performance.
4. *Integration with Existing Systems*: Seamless integration with supervisory control and data acquisition (SCADA) systems and existing protection schemes is essential for practical deployment in power grids.
5. *Concept Drift*: Transformers operate under varying conditions, leading to concept drift—where the relationship between input features and faults evolves. Adaptive models capable of handling concept drift are necessary to ensure ongoing reliability.

Interpretable machine learning models hold immense potential for enhancing transformer fault detection. While decision trees offer high interpretability, random forests and gradient boosting methods provide superior accuracy but require techniques such as feature importance and SHAP values to improve interpretability. SVMs, used in this study as a comparative baseline, provide a balanced approach between performance and efficiency, with moderate interpretability. Future research should focus on hybrid approaches that combine traditional diagnostic methods' strengths with ML models' flexibility and power. Addressing challenges such as real-time processing, data quality, and concept drift will further unlock the potential of these models, ensuring more reliable and transparent fault detection systems for power grids.

Further investigation of diverse, real-world datasets is crucial for validating these models' long-term performance and adaptability [27,28]. Exploring advanced data balancing techniques and cost-effective solutions for handling imbalanced datasets remains a priority [24–26,37,38]. Developing methods that can effectively address the noisy and uncertain nature of voltage signals is also essential for improving the accuracy and reliability of data-driven fault diagnosis [29,30].

The remainder of this paper is structured as follows: Section 2 discusses the methodology, including data preprocessing, feature extraction, and model selection. Section 3 presents the experimental setup and results, followed by a detailed discussion in Section 4. Section 5 concludes the study and suggests directions for future work.

2. Materials and Methods

2.1. Experimental Setup

A laboratory-scale, three-phase power transformer system was designed and constructed to simulate various healthy and faulty operating conditions. The setup, illustrated in Figure 1, replicates real-world scenarios to ensure accurate and representative data collection.

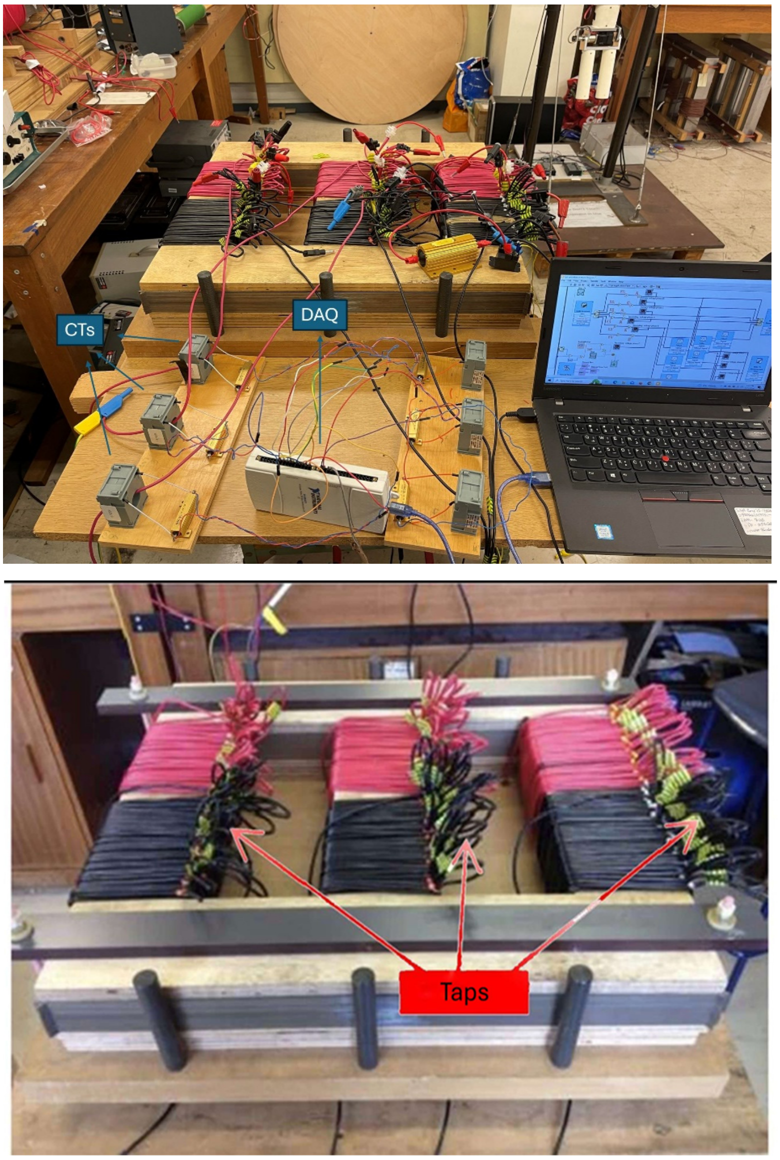

Figure 1. Schematic of the system in the laboratory.

- **Power Transformer**: The central element of the system was a five kVA, 416 V/240 V, delta-wye-connected three-phase power transformer. This configuration reflects transformers commonly deployed in electrical distribution systems, allowing for the investigation of a wide range of fault types relevant to practical, real-world applications. The transformer was carefully calibrated to ensure reliable performance under different fault conditions.

- **Voltage Sensors**: High-precision voltage sensors were deployed to ensure accurate capture of voltage signals. These sensors were connected as follows:
    - **Phase-to-Neutral Voltages** (V_a, V_b, V_c) were measured on the secondary side of the transformer to monitor individual phase behavior under different operating conditions;
    - **Line-to-Line Voltages** (V_{ab}, V_{bc}, V_{ca}) were also measured on the secondary side, allowing for the detection of interphase faults and providing a comprehensive view of transformer performance.
- **Data Acquisition System (DAQ)**: A National Instruments (NI) DAQ system was employed for data acquisition, ensuring high-resolution and reliable data capture. Key DAQ specifications include:
    - Model: NI USB-6212.
    - **Sampling Rate**: A sampling rate of 1 kHz was selected, ensuring that steady-state and transient voltage variations were captured during fault events. This sampling rate is sufficient to capture the fast dynamics of the fault transients, providing a detailed dataset for analysis.
    - **Simultaneous Acquisition**: All six voltage signals (three-phase and three-line voltages) were acquired simultaneously to maintain precise time alignment and ensure data consistency across all signals. This approach was necessary to avoid data skewing and ensure that machine learning models would be trained with synchronized and reliable data.
    - **LabVIEW Integration**: The DAQ system interfaced with LabVIEW software, enabling real-time data visualization, storage, and export.
- **Data Preprocessing**: The acquired voltage signals were filtered to reduce noise and uncertainties:
    - Filtering: A fourth-order Butterworth low-pass filter with a cutoff frequency of 500 Hz was applied to each voltage channel to remove high-frequency noise while preserving fault-related transients.
    - File Storage: Filtered data were saved to structured files, ensuring compatibility with MATLAB and Python for further analysis.
- **Fault Simulation Unit**: A dedicated fault simulation unit was integrated into the system to introduce various fault conditions safely and in a controlled manner. The unit was capable of simulating multiple fault types, including:
    - Single Line-to-Ground (SLG) Faults;
    - Line-to-Line (LL) Faults;
    - Turn-to-Ground (TG) Faults;
    - Turn-to-Turn (TT) Faults.

This unit allowed for precise control over fault impedance and location, enabling the study of different fault severities and their corresponding voltage signatures.

- **Computer and Data Analysis Software**: A laptop running LabVIEW software interfaced with the DAQ system to facilitate real-time monitoring and data acquisition. Key details include:
    - Data Storage: The recorded data were saved in a structured format suitable for further analysis.
    - Analysis Pipeline: The stored data were imported into Python and MATLAB to preprocess and apply advanced machine learning techniques.

2.2. Fault Simulation and Characterization

Various fault conditions commonly encountered in power transformers were carefully simulated to generate a comprehensive and representative dataset for training and evaluating the machine learning models. These simulations aimed to induce distinct voltage signatures, allowing the models to learn the subtle but characteristic changes in voltage behavior associated with each fault type. Each fault scenario was meticulously designed to capture various fault severities and corresponding voltage deviations, ensuring robust model performance under real-world conditions.

1. **Single-Line-to-Ground (SLG) Faults**

Single-line-to-ground faults are among the most frequent in power systems, occurring when one phase is directly connected to the ground. A controlled resistance (R_f) was inserted between a selected phase (A, B, or C) and the ground to simulate SLG faults. By varying the value of R_f, a spectrum of fault severities was replicated. Lower R_f values simulated bolted faults, which produce high fault currents and cause a pronounced voltage to drop in the faulted phase, alongside potential voltage rises in the healthy phases due to ground potential rise. Conversely, higher R_f values represented high-resistance faults, which result in more subtle voltage deviations, making them more challenging to detect. This comprehensive range of SLG fault conditions ensured that the machine learning models could effectively learn both obvious and subtle fault scenarios.

2. **Line-to-Line (LL) Faults**

Line-to-Line faults occur when two phases come into direct contact, forming a short circuit. These faults were simulated by connecting a controlled resistance (R_f) between pairs of phases (A-B, B-C, or C-A). By varying R_f, the fault's severity was adjusted, allowing the investigation of different fault intensities. Line-to-line faults typically result in significant voltage drops in the faulted phases, while the healthy phase may experience voltage fluctuations depending on the system's grounding configuration. These simulations ensured the machine learning models could effectively detect LL faults across various severities.

3. **Turn-to-Ground (TG) Faults**

Turn-to-ground faults involve a short circuit between a winding turn and the transformer core or tank, often due to insulation breakdown. These faults were simulated by connecting a selected turn on the secondary winding to the ground through a controlled resistance (R_f). The location of the faulted turn was varied along the winding to assess its impact on the voltage signatures. Turn-to-ground faults can cause localized distortions in the voltage waveform, potentially generating harmonics and interharmonics. The fault impedance and the position of the fault within the winding influence the severity of these distortions. These variations were critical for ensuring the machine learning models can detect faults that may not exhibit obvious voltage drops but still pose significant operational risks.

4. **Turn-to-Turn (TT) Faults**

Turn-to-turn faults are characterized by short circuits between adjacent turns within a winding, often serving as precursors to more severe faults. These faults were simulated by short-circuiting a specific number of adjacent turns on the secondary winding. The number of shorted turns was varied to simulate different fault severities. Turn-to-turn faults lead to circulating currents within the affected winding, causing localized heating and potentially generating harmonics in the voltage waveform. The magnitude of these effects is directly related to the number of shorted turns and their location within the winding. Simulating TT faults at different severities ensured that the machine learning models could recognize early-stage faults that may escalate into more critical conditions.

For each fault type, voltage data were recorded at multiple levels of R_f and at various time intervals after fault initiation. This approach enabled the capture of both transient and quasi-steady-state voltage responses, providing a comprehensive representation of the transformer's dynamic behavior under fault conditions. The simultaneous recording of all six voltage parameters (V_a, V_b, V_c, V_{ab}, V_{bc}, V_{ca}) ensured a holistic view of the voltage variations induced by each fault scenario. The high-resolution voltage measurements provided by this protocol were critical for capturing the nuanced and complex signatures associated with different fault severities.

This carefully designed fault simulation protocol and high-resolution voltage measurements produced a rich and diverse dataset. The dataset captures the intricate voltage responses under various fault conditions and severities, providing the necessary depth and quality for training and evaluating machine learning models. By simulating faults with varying resistance levels and severities, the models were exposed to various fault scenarios, enabling them to learn the subtle and complex voltage signatures associated with different fault types in power transformers. This comprehensive dataset lays a robust foundation for developing reliable, real-world fault detection models.

2.3. Data Acquisition

This section outlines the detailed process of acquiring voltage data from the experimental setup under healthy (normal operating) and simulated fault conditions. Careful attention was given to collecting accurate and representative data to train and evaluate the machine learning models effectively.

2.3.1. Healthy Condition Data

To establish a robust baseline for comparison, voltage data were collected under healthy operating conditions. The transformer was connected to a balanced three-phase resistive load, operating at its rated voltage and frequency. The data acquisition system was configured with a 1 kHz sampling rate, capturing all six voltage signals—three phase-to-neutral voltages (V_a, V_b, V_c) and three line-to-line voltages (V_{ab}, V_{bc}, V_{ca}).

- Duration: Voltage signals were recorded continuously for 15 min per session, repeated over ten separate sessions on different days to ensure variability in normal operating conditions. This resulted in 150 min of healthy data.
- Purpose: The extended duration and repeated sessions ensured that steady-state voltage characteristics under various environmental conditions were well represented in the dataset, providing a robust foundation for training machine learning models.
- Consistency: Elapsed time tracking in the LabVIEW software ensured uniformity across all acquisition sessions, and any anomalies during data collection were flagged and re-recorded.

2.3.2. Fault Condition Data

The fault simulation unit systematically simulated various fault conditions, as detailed in Section 2.2. This unit created a comprehensive dataset representing common transformer fault types.

Voltage data were acquired under various fault severities by varying fault impedance or the number of shorted turns (for TT faults).

- Duration: Voltage signals were recorded for 5 min per fault type, repeated over five independent sessions per fault type, resulting in 100 min of faulty data.
- Sampling Rate: All six voltage parameters (V_a, V_b, V_c, V_{ab}, V_{bc}, V_{ca}) were recorded simultaneously at a 1 kHz sampling rate, ensuring the capture of transient and steady-state responses associated with each fault.
- Time Frame: The recordings were designed to capture both the transient phase immediately after fault initiation and the subsequent steady-state conditions, ensuring comprehensive data for model training.
- Consistency: As with the healthy condition data, elapsed time tracking ensured consistency across fault simulations, and repeated sessions accounted for variability in fault characteristics.

2.3.3. Summary of Data Acquisition

The meticulous data acquisition process resulted in a high-quality dataset:

- Healthy Conditions: 150 min of data representing balanced voltage profiles and steady-state transformer operation;
- Fault Conditions: 100 min of data representing unbalanced and distorted voltage patterns indicative of specific fault types and severities.

The dataset provides a robust foundation for training and validating the machine learning models, ensuring they can accurately distinguish between healthy and faulty transformer behaviors across various conditions

2.4. Data Preprocessing

The raw voltage data collected from the experimental setup underwent a series of preprocessing steps to ensure data quality and consistency. These steps were designed to enhance the reliability and robustness of the machine learning models by eliminating noise, outliers, and inconsistencies.

2.4.1. Outlier Removal

Outliers in the voltage data, arising from transient disturbances, sensor malfunctions, or measurement errors, can negatively affect the training of machine learning models. A two-step outlier removal process was implemented:

1. Visual Inspection: Voltage signals for each channel were visually inspected for apparent outliers, such as sudden voltage spikes or abrupt changes that were inconsistent with normal operating or fault conditions.
2. Statistical Thresholding: A statistical thresholding technique was applied to detect less obvious outliers. Data points exceeding three standard deviations from the mean voltage for each channel were flagged as outliers and replaced with the average of adjacent data points. This approach preserved the temporal consistency of the voltage signals while minimizing the impact of abnormal data points.

2.4.2. Noise Filtering

A fourth-order Butterworth low-pass filter was applied to each voltage channel to reduce noise from electromagnetic interference and sensor limitations. The filter's cutoff frequency was 500 Hz, effectively attenuating high-frequency noise components while preserving the essential voltage characteristics relevant for fault detection. This noise-filtering process ensured that the machine learning models would be trained on cleaner, more reliable data.

2.4.3. Data Normalization

All voltage data were normalized using min-max normalization to prevent features with larger voltage magnitudes from disproportionately influencing the model's learning process. This method scaled the voltage values to a range between 0 and 1, ensuring that all six voltage features (V_a, V_b, V_c, V_{ab}, V_{bc}, V_{ca}) contributed equally during model training. The normalization formula used was

$$\text{Normalized Value} = \frac{\text{Value} - \text{Min Value}}{\text{Max Value} - \text{Min Value}} \tag{1}$$

Value is the original voltage data point. **Min Value** and **Max Values** represent the minimum and maximum observed voltage values for each feature across the dataset. This step ensured that the machine learning models could effectively learn from each feature without bias towards any specific voltage parameter.

These preprocessing steps—outlier removal, noise filtering, and data normalization—ensured that the voltage data used for training the machine learning models were high quality, free from noise and outliers, and appropriately scaled. This preprocessing process was critical in enhancing the models' performance and robustness.

2.5. Feature Selection

The choice of features used as inputs to the machine learning models was carefully considered to ensure the models' ability to discern between different fault types. The three-phase voltages (V_a, V_b, V_c) were selected as input features due to their sensitivity to various transformer fault conditions.

- **SLG Faults** typically cause a significant voltage to drop in the faulted phase and may lead to voltage rises in the healthy phases.
- **LL Faults** result in voltage sags on the faulted phases and can introduce imbalances in the healthy phase.
- **TG and TT Faults** lead to localized voltage distortions and imbalances, potentially generating harmonics.

By including these raw phase voltages as features, the machine learning models can recognize the distinct voltage patterns associated with each fault type, facilitating more accurate fault diagnosis.

2.6. Classification Models

Three machine learning models—decision trees, support vector machines (SVM), and logistic regression—were chosen for this study due to their strengths in handling the complexities of transformer fault detection. These models are adept at managing nonlinearities, imbalanced fault classes, and real-time classification needs.

2.6.1. Decision Tree

Decision trees are nonparametric supervised learning algorithms well suited to transformer fault detection due to their ability to handle nonlinear relationships and imbalanced datasets often encountered in such applications. They recursively partition the dataset based on feature values, aiming to create homogeneous groups at each leaf node [39]. At each node, the algorithm selects the feature that maximizes information gain (or minimizes impurity, using metrics like Gini impurity or entropy) [40,41]. This process results in a hierarchical tree structure that serves as an interpretable flowchart for classification. The tree's interpretability allows for clearly identifying the relationships between voltage features and fault classifications, aiding in understanding the underlying causes of faults. Furthermore, decision trees are computationally efficient, supporting real-time classification requirements. To mitigate overfitting, particularly in complex datasets, the maximum depth of the tree is optimized using 5-fold cross-validation in this study.

Mathematical Model:

A decision tree classifies data by recursively splitting the feature space. At each node, the algorithm selects the feature X_j and threshold t that best separate the data into two subsets, aiming to minimize impurity measures such as the Gini index [39,42]:

$$G = 1 - \sum_{k=1}^{K} p_k^2 \tag{2}$$

where p_k the proportion of instances belonging to a class k at a given node. The process continues until a stopping criterion, such as maximum depth or minimum samples per leaf, is met.

2.6.2. Support Vector Machine (SVM)

Support vector machines (SVMs) are powerful supervised learning models known for their ability to handle high-dimensional data and effectively classify complex patterns, making them suitable for transformer fault detection. SVMs aim to find an optimal hyperplane that maximizes the margin between different fault classes [43]. The support vectors define this hyperplane, the data points closest to the decision boundary [44]. This margin maximization principle enhances the model's robustness to noise and variations in the input voltage signals, which is crucial in real-world applications. Furthermore, SVMs are well suited for handling the potentially overlapping fault classes often observed in transformer fault data. This study uses an SVM with a radial basis function (RBF) kernel, allowing the model to capture nonlinear relationships between voltage features and fault conditions. The critical hyperparameters of the RBF kernel, C (cost) and gamma (kernel width), are optimized using 5-fold cross-validation to achieve optimal performance.

Mathematical Model:

SVMs seek to solve the optimization problem [43,45]:

$$\min_{\mathrm{w,b}} \frac{1}{2}|\mathbf{w}|^2 \text{ subject to } \mathrm{y_i}\left(\mathrm{w}^\top \mathbf{x_i} + \mathrm{b}\right) \geq 1,\ \forall \mathrm{i} \tag{3}$$

where w is the weight vector, b is the bias term, y_i are the class labels, and x_i are the feature vectors. The kernel trick maps for nonlinear classification input data into a higher-dimensional space. The radial basis function (RBF) kernel is defined as:

$$K(x_i, x_j) = \exp\left(-\gamma|x_i - x_j|^2\right) \tag{4}$$

where γ controls the width of the kernel.

2.6.3. Logistic Regression

Logistic regression is a widely used method for binary classification, estimating the probability that a given sample belongs to a particular class, such as determining whether a transformer is healthy or faulty [46]. However, transformer faults often exhibit a multi-class nature (e.g., single line-to-ground, line-to-line), requiring the one-vs-rest strategy to adapt logistic regression to this problem. The method applies a sigmoid function to map a linear combination of input features to a probability score, which makes it practical for binary classification tasks. Model parameters are learned by maximizing the log-likelihood function, enhancing its effectiveness. Additionally, logistic regression provides a computationally efficient approach for fault classification, making it highly suitable for real-time applications. Although simpler than decision trees and SVMs, it offers interpretability by highlighting the significance of specific voltage features in fault detection, offering a balance between simplicity and insight.

Mathematical Model:

Logistic regression models the probability of class membership as [47,48]:

$$P(y = 1 \mid x) = \frac{1}{1 + \exp\left(-\left(w^\top \boldsymbol{x} + b\right)\right)} \tag{5}$$

where $\boldsymbol{w}$ is the weight vector, b is the bias term, and $\boldsymbol{x}$ is the feature vector. The parameters $\boldsymbol{w}$ and b are estimated by maximizing the log-likelihood function:

$$\mathcal{L}(w, b) = \sum_{i=1}^{N}[y_i \log P(y = 1 \mid x_i) + (1 - y_i) \log P(y = 0 \mid x_i)] \tag{6}$$

This approach optimizes the model parameters to fit the observed data best.

Table 2 summarizes the hyperparameters and their optimized values for the models used in this study.

All three models—decision trees, SVM, and logistic regression—were selected for their complementary strengths in interpretability, nonlinearity handling, imbalance management, and computational efficiency. To enhance model performance further, 5-fold cross-validation and grid search were employed for hyperparameter tuning. This optimization focused on critical parameters such as C and gamma in SVM, maximum depth in decision trees, and regularization strength (C) in logistic regression.

Table 2. Optimized hyperparameters for machine learning models.

Model	Hyperparameter	Description	Optimized Value
Decision Tree	Max Depth	Maximum depth of the tree to prevent overfitting	10
	Criterion	Split criterion	Gini Index
	Min Samples Split	Minimum samples required to split an internal node	2
SVM (RBF Kernel)	C	Cost parameter controlling margin violations	1.0
	Gamma	Kernel width, controlling the decision boundary	0.1
	Kernel	Kernel type for nonlinear feature mapping	RBF
Logistic Regression	C	Inverse regularization strength	1.0
	Solver	Algorithm to optimize the log-likelihood function	lbfgs
	Multiclass Strategy	Method to handle multiclass classification	One-vs-Rest

Note: Hyperparameters were optimized using grid search with 5-fold cross-validation. Accuracy was used as the primary metric for optimization.

Moreover, the features used in these models are derived from time–frequency analysis techniques, particularly wavelet transforms. These transforms effectively decompose the voltage signal into time–frequency components, providing critical insights into the underlying fault patterns. The nonlinear nature of these features aligns well with the modeling capabilities of SVM and decision trees, which excel in capturing complex relationships within the data. Consequently, the extracted features from Section 2.5 directly inform the choice and optimization of these models, reinforcing their effectiveness in fault classification.

2.7. Model Training and Validation

To ensure the robustness and generalization capability of the machine learning models, a k-fold cross-validation technique was employed during the training and evaluation process. This approach mitigates the risk of overfitting, ensuring the models perform well on unseen data while providing a reliable estimate of their generalization capabilities.

2.7.1. Data Allocation and K-Fold Cross-Validation Procedure

K-fold cross-validation involves partitioning the dataset into k equal-sized folds. This study's dataset consisted of 6000 samples, with 1500 samples representing various fault conditions and 4500 samples representing healthy transformer conditions. This ratio (25% faults, 75% healthy) reflects real-world scenarios where fault instances are significantly rarer than healthy conditions.

To ensure a balanced representation of both healthy and faulty samples in each fold:

- The dataset was stratified during partitioning. Stratification ensures that each fold contains the same proportion of healthy and faulty samples (75% healthy, 25% faults), maintaining the class distribution across all folds.
- This stratified approach ensures that the models are exposed to diverse fault scenarios in the training and validation phases, reducing bias and improving fault detection performance on imbalanced data.

The steps involved in k-fold cross-validation are as follows:

1. Shuffle the dataset randomly to avoid any inherent ordering that could bias model training.

2. Split the dataset into k = 5 equal-sized folds, ensuring each fold maintains the original class distribution (stratification).
3. For each fold:
    - Use the current fold as the validation set;
    - Use the remaining *k-1* folds as the training set;
    - Train the model on the training set;
    - Evaluate the model's performance on the validation set.
4. Average the performance metrics across all k folds to obtain a comprehensive estimate of the model's generalization performance.

Cross-validation ensures fair evaluation by maintaining stratification, particularly in handling the imbalance between healthy and faulty data samples.

2.7.2. Choice of k

This study employed 5-fold cross-validation (k = 5). The decision to use k = 5 was based on the following considerations:

- Computational Efficiency: Using five folds offers a practical balance between accuracy and computational cost. Higher values of K (e.g., 10-fold cross-validation) provide slightly more precise estimates but at the cost of increased computational time, particularly when training multiple models and optimizing hyperparameters.
- Reliable Performance Estimation: Previous studies in similar domains indicate that 5-fold cross-validation provides a robust estimate of model performance without introducing significant bias or variance in the evaluation metrics.
- Dataset Size: With 6000 samples, splitting the data into five folds ensures sufficient samples in the training and validation sets, preserving statistical representativeness.

By employing 5-fold cross-validation, we ensured that each model was trained and evaluated on multiple subsets of the data, minimizing the likelihood of overfitting and providing an accurate assessment of their ability to generalize to unseen data. Stratified sampling within each fold also maintained the class distribution, ensuring a balanced evaluation for fault and healthy conditions.

2.8. Performance Evaluation Metrics

A comprehensive set of evaluation metrics was employed to rigorously assess the performance of the trained machine learning models. These metrics provide insights into the models' capabilities, allowing for a thorough comparison and selection of the best-performing model. The evaluation is based on the confusion matrix, which summarizes the model's predictions against the actual class labels. For a binary classification problem, the confusion matrix consists of four elements:

- True Positives (TP): correctly classified faulty instances;
- True Negatives (TN): correctly classified healthy instances;
- False Positives (FP): healthy instances incorrectly classified as faulty (type I error);
- False Negatives (FN): faulty instances incorrectly classified as healthy (type II error).

The performance metrics of the three machine learning models evaluated using 5-fold cross-validation are presented in Table 3.

These metrics provide a holistic view of the models' performance:

- Sensitivity: measures the model's ability to correctly identify faulty transformers;
- Specificity: measures the model's ability to correctly identify healthy transformers;
- Precision: quantifies the proportion of correctly identified faulty transformers out of those classified as faulty;
- NPV: represents the proportion of correctly identified healthy transformers from those classified as healthy;
- Accuracy: indicates the overall proportion of correctly classified instances (both healthy and faulty);

- False Alarm Rate: the proportion of healthy transformers misclassified as faulty.

Considering this comprehensive set of metrics, the authors aim to select the model that best balances sensitivity, specificity, and accuracy while minimizing false alarms. This will ultimately lead to a reliable and practical fault detection system.

Table 3. Performance metrics of machine learning models for transformer fault detection.

Metric	Formula
Sensitivity (Detection Rate)	$Sensitivity = \frac{TP}{TP+FN}$
Specificity	$Specificity = \frac{TN}{TN+FP}$
Precision	$Precision = \frac{TP}{TP+FP}$
Negative Predictive Value (NPV)	$NPV = \frac{TN}{TN+FN}$
Accuracy	$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
False Alarm (FA)	$FA = 1 - Specificity$

The overall experimental setup and data acquisition process employed in this study are illustrated in Figure 2.

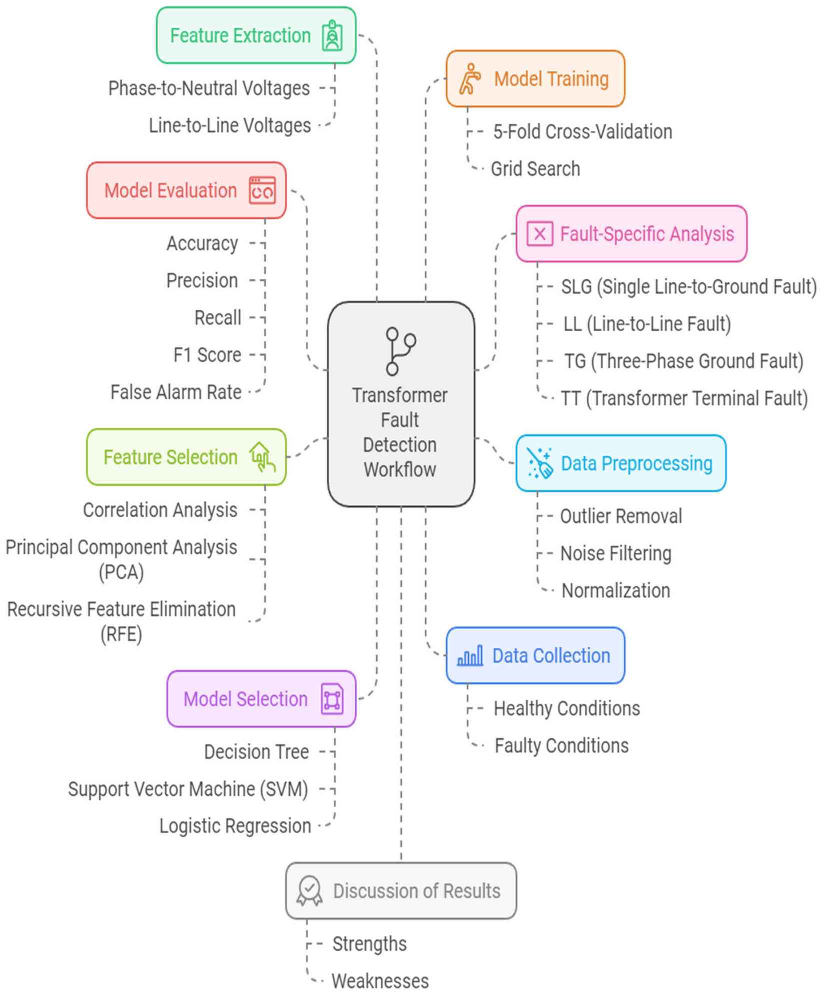

Figure 2. Workflow of the proposed machine learning framework for transformer fault detection.

The dataset used in this study is available upon reasonable request to ensure data privacy and compliance with institutional data-sharing policies. Researchers interested in accessing the data may contact the corresponding author with a detailed request outlining their intended use.

3. Results and Discussion

3.1. Model Performance

Five classification models were trained and evaluated using 5-fold cross-validation to determine the most suitable model for transformer fault detection. The models considered were decision trees (fine tree), decision trees (medium tree), decision trees (coarse tree), support vector machines (SVM), and logistic regression. The training dataset consisted of 6000 data points, with 1000 representing healthy transformer operation and 5000 representing various fault conditions (Figure 3).

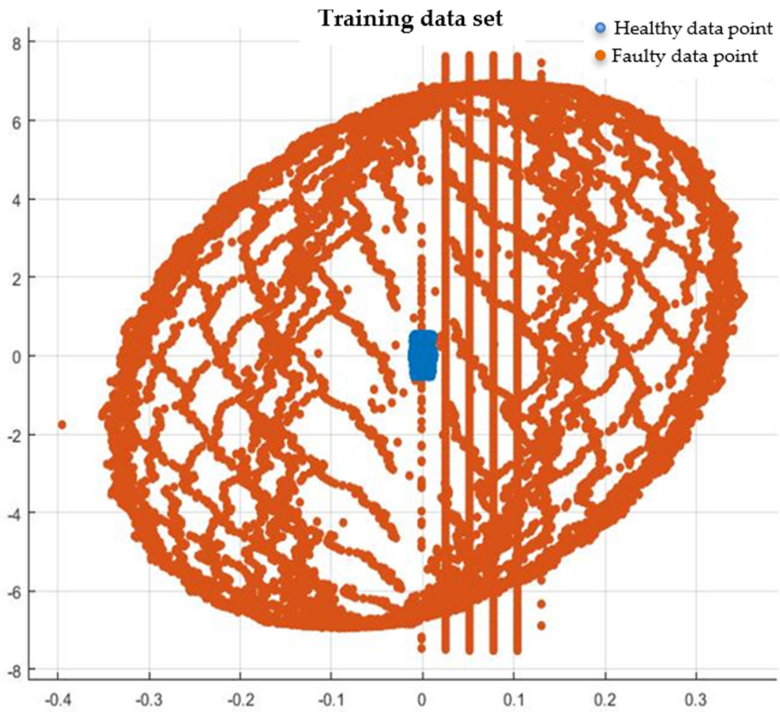

Figure 3. Data points used in the training stage.

Figure 3 displays a scatter plot showing the distribution of two selected features from our dataset, designated as column_1 on the *X*-axis and column_2 on the *Y*-axis. These features, while kept anonymous here, correspond to specific measurable aspects relevant to power transformer analysis and were chosen for their importance in improving classification accuracy. The values on both axes are likely scaled or normalized to enhance visualization and allow for better comparison. Each dot in the plot represents a single observation from the dataset, with colors distinguishing the classes: blue indicates class 0 (healthy operation), and orange represents class 1 (faulty conditions). The blue points (class 0) cluster tightly in one area, reflecting a consistent pattern associated with healthy operation, while the broader spread of orange points (class 1) suggests greater variability linked to different fault conditions. This visual separation highlights the usefulness of these features in differentiating between healthy and faulty transformer states, making them essential components in our classification modelling process.

Figure 4 presents the accuracy of each model obtained from cross-validation. The decision tree models, the fine tree and medium tree, achieved the highest mean accuracy, outperforming the other models.

The superior performance of the decision tree models suggests that their ability to capture nonlinear relationships and handle imbalanced datasets is advantageous for this specific fault detection task. A statistical analysis using a paired *t*-test revealed that the difference in performance between the fine tree and the SVM model was statistically significant ($p < 0.05$), further supporting the selection of the decision tree.

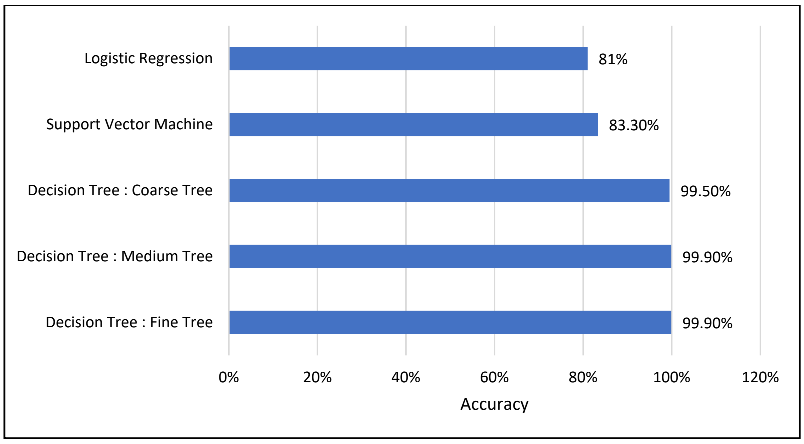

Figure 4. Accuracy of various classification models.

3.2. Performance on Unseen Data

The decision tree (fine tree) model, exhibiting the best performance in cross-validation, was selected for further evaluation on an unseen test set of 400 samples (200 healthy, 200 faulty). The confusion matrix is shown in Table 4, and the corresponding performance metrics are presented in Table 5.

Table 4. Confusion matrix (test set).

	Predicted Faulty	**Predicted Healthy**
Actual Faulty	TP = 183	FN = 17
Actual Healthy	FP = 3	TN = 197

Table 5. Performance metrics on the test set.

Metric	**Value**
Sensitivity (Detection Rate)	91.5%
Specificity	98.5%
Precision	98.39%
Negative Predictive Value (NPV)	92.05%
Accuracy	95%
False Alarm (FA)	1.5%

The fine tree model achieved an overall accuracy of 95% on the unseen test set, demonstrating good generalization capability. The confusion matrix reveals that the model correctly classified 183 out of 200 faulty samples (91.5% recall) and 197 out of 200 healthy samples (98.5% specificity). The model exhibits a low false positive rate (1.5%), indicating that healthy transformers are rarely misclassified as faulty. The slightly lower recall suggests that some fault conditions might be more challenging to detect using voltage signals alone. Further investigation is needed to determine the faults contributing to these false negatives.

3.3. Fault-Specific Performance

The fine tree model was further evaluated on a separate test set of 6000 faulty samples, with 1500 samples representing each of the four fault types: single line-to-ground (SLG), line-to-line (LL), turn-to-ground (TG), and turn-to-turn (TT). Table 6 presents the fault-specific detection accuracy.

Table 6. Fault-specific detection accuracy.

Fault Type	Number of Samples	Correctly Detected	Accuracy (%)
Single Line-to-Ground	1500	1390	92.67
Line-to-Line	1500	1318	87.87
Turn-to-Ground	1500	1383	92.20
Turn-to-Turn	1500	1340	89.33

As illustrated in Figure 5, while the model achieves high detection accuracy across all fault types (exceeding 87%), the performance varies. The model exhibits the highest accuracy for SLG (92.67%) and TG (92.20%) faults, which may be attributed to the more distinct voltage signatures produced by these ground faults [49,50]. The lower accuracy for LL faults (87.87%) suggests they exhibit more subtle voltage disturbances, making them more challenging to detect based on voltage signals alone.

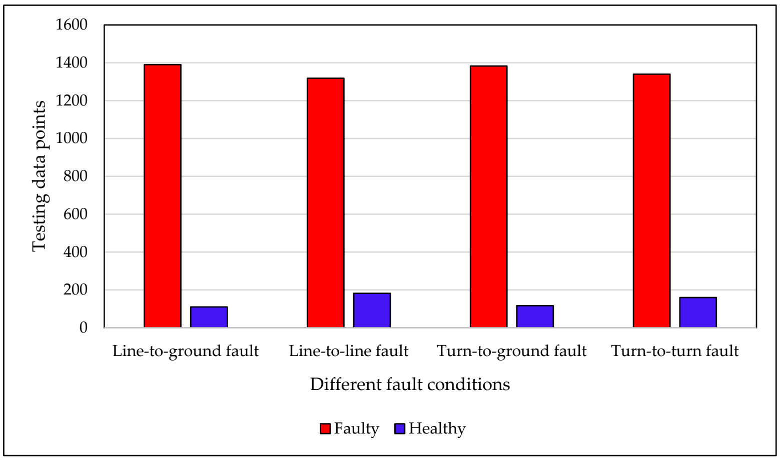

Figure 5. Testing data points for different fault conditions.

3.4. Performance on Healthy Condition Data

The fine tree model's performance was assessed on a combined test set of 12,000 samples (6000 healthy, 6000 faulty), including the fault-specific samples from Section 3.3. The confusion matrix is shown in Table 7, and the corresponding performance metrics are presented in Table 8.

The fine tree model achieved an overall accuracy of 95.03% on the combined test set. The model maintains a high specificity (99.53%), resulting in a meager false alarm rate (0.47%). This indicates that the model is highly reliable in identifying healthy transformers. The slightly lower sensitivity (90.52%) on this combined dataset, compared to the balanced test set described in Section 3.2, suggests that the inclusion of diverse fault types with varying voltage characteristics poses a more significant challenge for the model.

Table 7. Confusion matrix (combined test set).

	Predicted Faulty	Predicted Healthy
Actual Faulty	TP = 5431	FN = 569
Actual Healthy	FP = 28	TN = 5972

Table 8. Performance metrics on combined test set.

Metric	Value
Sensitivity (Detection Rate)	90.52%
Specificity	99.53%
Precision	99.49%
Negative Predictive Value (NPV)	91.30%
Accuracy	95.03%
False Alarm (FA)	0.47%

4. Discussion

This study demonstrates the effectiveness of machine learning, specifically the decision tree model, for detecting and classifying power transformer faults using voltage signals. In 5-fold cross-validation, the fine tree and medium tree variants achieved 99.90% accuracy. Based on these results, the fine tree model was selected for further evaluation. This high cross-validation accuracy, achieved using only voltage signals, suggests a cost-effective and practical alternative to methods requiring multiple data sources [51]. The fine tree model achieved 95% accuracy on a held-out test set, indicating good generalization capability. This robust performance, high sensitivity (91.5%), and specificity (98.5%) demonstrate the model's balanced ability to detect faulty and healthy conditions, minimizing missed faults and unnecessary interventions in real-world applications.

The fault-specific analysis provides further insights into the model's performance across different fault types:

- SLG and TG Faults: The model exhibits the highest accuracy for single line-to-ground (SLG) (92.67%) and turn-to-ground (TG) (92.20%) faults. This aligns with the understanding that ground faults produce distinct voltage signatures due to the direct connection between a phase and ground, causing significant voltage deviations [50].
- LL Faults: The model's accuracy for line-to-line (LL) faults (87.87%) is comparatively lower. LL faults occur when fault current flows between two phases without a direct path to the ground, resulting in smaller voltage deviations. These subtle disturbances make LL faults harder to distinguish from noise or standard operating variations. Addressing this challenge could involve integrating additional features, such as current signals or harmonic content, to improve detectability.

4.1. Practical Implications

1. Low False Positive Rate: The low false alarm rate (0.47%) on 6000 healthy transformer samples is a significant finding. This minimizes unnecessary maintenance, improving cost efficiency and grid operation while reducing disruptions in power systems.
2. Impact of Low Recall Rate for Healthy Samples: Although the model demonstrated high specificity, a low recall rate for healthy samples could lead to delayed fault detection, potentially increasing the risk of equipment damage and extending outage durations. The balanced performance metrics observed in this study mitigate these risks, achieving a practical tradeoff between sensitivity and specificity.

4.2. Limitations and Future Research

This study acknowledges several limitations that highlight opportunities for future research:

1. Laboratory-Scale Setup: The controlled environment of a laboratory-scale transformer enabled the generation of diverse fault conditions and a clean dataset. However, this setup may not fully represent the complexities of real-world power systems, such as variations in operating conditions, noise, and transformer designs. Future work will focus on validating the model using real-world data from operational transformers to assess its performance under more realistic conditions.

2. Lack of Real-World Data: Real-world datasets typically include challenges such as imbalanced fault occurrence rates, environmental noise, and unmodeled system dynamics. Collecting and analyzing larger, more heterogeneous datasets will be crucial for refining and generalizing the proposed framework.
3. Noise and Voltage Signal Imbalances: Real-world transformer data often include noise from electromagnetic interference, sensor inaccuracies, and transient disturbances. These noise sources can obscure the subtle voltage variations characteristic of certain fault types, particularly LL faults. Future research should prioritize developing robust preprocessing techniques, such as adaptive filtering and time–frequency feature engineering, to mitigate the impact of noise and voltage imbalances.
4. Limited Feature Set: This study relies solely on voltage signals, which proved effective for fault detection but may not fully capture all relevant fault characteristics. Expanding the feature set to include current signals, harmonic content, or thermal data could enhance the model's ability to discern subtle faults and improve overall accuracy.

4.3. Comparison with Existing Literature on Transformer Fault Detection

Transformer fault detection is vital for maintaining the reliability and safety of power grids. Researchers have proposed various machine learning and deep learning approaches to enhance the accuracy and robustness of fault detection. Table 9 compares state-of-the-art methods based on performance metrics, highlighting their unique strengths and limitations alongside this study's decision tree model.

Table 9. Comparison of transformer fault detection methods.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Reference Paper Title	Ref.
Transformer Encoder (ECG Signals)	99%	100%	98.1%	99%	Unsupervised Transformer-Based Anomaly Detection in ECG Signals	[52]
Convolutional–Transformer Model	>99%	>99%	>99%	>99%	Convolutional–Transformer Model with Long-Range Temporal Dependencies for Bearing Fault Diagnosis Using Vibration Signals	[53]
CNN + LSTM	98.86%	98.86%	98.90%	98.88%	Intelligent Fault Detection and Classification Based on Hybrid Deep Learning Methods for Hardware-in-the-Loop Test of Automotive Software Systems	[54]
CNN	99.95%	94%	97%	94%	Convolutional Neural Network-Based Transformer Fault Diagnosis Using Vibration Signals	[55]
RNN	95.6%	85%	90%	87%	The State of the Art in Transformer Fault Diagnosis with Artificial Intelligence and Dissolved Gas Analysis: A Review of the Literature	[56]
DBN	96.4%	90%	92%	91%	Deep Learning in High Voltage Engineering: A Literature Review	[57]
SAAT	90.1%	80%	85%	82%	Deep Learning in High Voltage Engineering: A Literature Review	[57]
Decision Tree Model	95.03	99.49	90.52	94.99	Transformer Fault Detection Using Decision Trees on Voltage Signals	(this study)

Table 9 illustrates the wide variety of approaches available for transformer fault detection, each with specific advantages and limitations:

1. Deep Learning Architectures:
   - Transformer Encoder: Achieves near-perfect metrics (accuracy: 99%, precision: 100%), showcasing its capability for anomaly detection in time-series data like

ECG signals. While highly effective, its generalization to transformer-specific data requires further investigation.
  - Convolutional–Transformer Model: Combines the strengths of convolutional neural networks (CNNs) and transformers, resulting in exceptional performance across all metrics (>99%). Its ability to capture long-range dependencies makes it particularly suitable for vibration signal analysis.
  - CNN + LSTM: Combines spatial feature extraction (via CNN) with temporal analysis (via LSTM), delivering strong overall performance (accuracy: 98.86%) for hardware-in-the-loop testing.
2. Machine Learning Models:
  - Decision Tree (This Study): Demonstrates high precision (99.49%) and competitive accuracy (95.03%), emphasizing its effectiveness in detecting transformer faults with minimal false positives. Its interpretability and computational efficiency make it particularly appealing for real-world deployment. However, it shows a slightly lower recall (90.52%) for faults with subtle voltage deviations, such as line-to-line (LL).
  - RNN and DBN: While less accurate than CNN-based models, these methods (accuracy: 95.6% and 96.4%, respectively) offer robust classification capabilities for transformer faults. Their reliance on dissolved gas analysis (DGA) data makes them suitable for applications focused on chemical fault indicators.
  - SAAT: Achieves moderate performance (accuracy: 90.1%) but is limited by lower precision and F1-scores, suggesting potential challenges in handling complex fault scenarios.
3. Traditional vs. Advanced Methods:
  - Deep learning architectures like the convolutional–transformer and CNN + LSTM models consistently outperform traditional machine learning models regarding overall metrics. However, they require extensive computational resources and larger datasets and can be less interpretable.
  - The decision tree model balances computational efficiency, interpretability, and accuracy, making it an excellent choice for cost-sensitive applications or environments with limited computational power.

5. Conclusions

This study demonstrates the potential for a cost-effective and reliable power transformer fault detection solution using machine learning. Specifically, the tree model, specifically the fine tree variant, achieved robust performance with 95% accuracy on a held-out test set and low false alarm rates (0.47%). These findings highlight the practicality of leveraging voltage signals alone to classify faults effectively. The fault-specific analysis revealed high accuracy for SLG (92.67%) and TG (92.20%) faults due to their distinct voltage signatures while identifying challenges in detecting LL faults (87.87%), which produce subtler voltage deviations.

These results underscore the practical value of this approach in minimizing unnecessary maintenance, improving cost efficiency, and enhancing grid reliability by effectively differentiating between faulty and healthy transformer conditions. The low false positive rate ensures smoother grid operation while conserving resources, further reinforcing the framework's potential for real-world deployment.

Despite these promising findings, this study acknowledges limitations, including the controlled laboratory-scale setup and the exclusive reliance on voltage signals, which may not fully capture real-world complexities. Addressing these limitations is critical for advancing the proposed framework's practical applicability.

Future Research Directions

Building on this foundation, future work should focus on the following areas:

1. Validation of Real-World Data: As a first step, extending the analysis to datasets collected from operational transformers in diverse environments is crucial to assess the model's robustness under realistic conditions, including noise and dynamic operating states.
2. Integration of Additional Data Sources: Incorporating data from complementary monitoring systems, such as dissolved gas analysis (DGA) and acoustic emission (AE) sensors, could provide a more comprehensive understanding of fault dynamics and enhance model performance, particularly for subtle faults like LL faults.
3. Exploration of Advanced Machine Learning Techniques: Investigating deep learning architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), could improve the ability to capture complex relationships in fault data and enhance classification accuracy across all fault types.
4. Development of Online Fault Detection Capabilities: A key area for future investigation is the development of real-time fault detection systems that integrate the proposed framework into online monitoring platforms, enabling timely identification and mitigation of transformer faults.
5. Cost–Benefit Analysis: A detailed economic analysis of the proposed approach's operational benefits is essential. Quantifying cost savings from reduced false positives, improved maintenance scheduling, and enhanced fault detection accuracy will provide practical insights into its long-term value.

Addressing these areas allows the proposed framework to be refined and scaled to meet the demands of real-world power systems, offering a robust and scalable solution for transformer fault detection. These advancements will contribute to more reliable, cost-effective, and resilient grid operations, ensuring power systems' continued safety and efficiency in the face of evolving energy demands and grid modernization efforts.

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