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Transformer Fault Diagnosis through Machine Learning

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***Abstract*— Power transformers, crucial electrical network components, must perform reliably to maintain system stability. Transformer problems that are not correctly identified and classified can cause substantial interruptions and expensive repairs. This research proposes a transformer fault classification machine learning algorithm using failure history data and advanced pattern recognition. The suggested transformer operating situation classification approach uses decision trees, SVMs, and LDAs. Data is preprocessed to improve classification accuracy, and wavelet transform feature extraction is used. 5-fold validation checks model performance. The results show that machine learning enhances predictive maintenance, grid dependability, and transformer health monitoring.**

***Index Terms*— Transformer fault classification, Machine learning.**

I. INTRODUCTION

Transformers help power networks efficiently transmit and distribute electricity across voltage levels. Substations depend on them, therefore their reliability affects system performance. Transformers need internal and exterior failure protection to maintain power and equipment life. Internal concerns include short circuits, overheating, partial discharges, and failing insulation might threaten their operating reliability. Timely and accurate problem identification extends transformer life, reduces maintenance costs, and prevents catastrophic failures. Traditional diagnostic methods like FRA and DGA provide valuable information, but accuracy and real-time application are often issues. Machine learning and signal processing advances have made data-driven fault classification and detection useful. Through faults are external faults that cause excessive transformer current without differential protection. Short circuits or phase-to-ground network disruptions can cause these failures. feeder lines linked. Transformers can sustain such loads within short-circuit tolerance limits, but repeated exposure promotes insulation and winding degradation.
K. Premalatha et al. studied transformer failure classification and diagnosis using machine learning [1]. Traditional fault identification methods were shown to be inaccurate and slow. The authors use historical and contemporary data to classify transformer faults using machine learning. A. Vyshnavi et al. found wavelet transform-based feature extraction for equipment failure diagnostics effective in managing complex and non-stationary data [2]. The study compares wavelet-based fault classification approaches utilising machine learning. They prioritised advanced signal processing for accurate defect identification. Hailong Ma et al. developed a new power transformer latent fault detection method to improve fault diagnosis [3]. A fault detection system using an IPSO algorithm and a BP neural network was proposed. They used dynamic inertia weight modulation and nonlinear learning factor modification to avoid premature convergence and improve optimisation in traditional PSO. A. Balan et al. [4] diagnose transformer faults using machine learning.

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Conventional transformer failure diagnosis methods were shown to be inefficient and inaccurate. Data-driven machine learning improved fault prediction and classification in the study. H. Hadiki, F. S. Hasnaoui, and S. Georges studied transformer defect prediction using machine learning [5]. Traditional defect detection technologies were evaluated for precision, reaction time, and maintenance cost. A machine learning-based prediction algorithm that uses transformer data to predict faults was proposed. T.-H. Han et al. developed a three-phase transformer-type Superconducting Fault Current Limiter (SFCL) to limit power system fault currents [6]. Their research focusses on restricting three-phase ground fault currents efficiently to improve electrical system safety and stability. An innovative fault current mitigation method uses two superconducting modules (SCMs) integrated in a three-phase transformer's secondary windings [6]. By tackling the any-shot learning problem, Yue Zhuo et al. solved industrial fault diagnostic problems with scarce or unobtainable defect samples [7]. The experts suggested using Generative Adversarial Networks to avoid this issue. By collecting many samples for various conditions, this helped construct a viable diagnostic model. J. H. Estrada et al. developed a new transformer failure evaluation method using magnetic flux entropy to detect distortions, ageing, overloading, and harmonics [8]. Using entropy ideas, the study measured transformer prototype thermal and magnetic fluxes non-invasively.

This research work utilizes wavelet transform for feature extraction from the current and voltage of the transformer. The primary contributions of this paper have been summarized below:

- A diverse dataset of transformer operating conditions is generated
- Wavelet transform is implemented to extract features.
- Machine learning algorithms have been trained with the extracted features.
- Accuracy of the trained model has been assessed through 5-fold validations.

The rest of the paper is organized as: The methodology of the proposed framework is decribed in section 2 while section 3 elaborates the mathematics of LDA. The results of proposed framework are discussed in section 4 while section 5 provides the concluding remarks.

II. METHODOLOGY

This paper presents a machine learning framework for transformer defect diagnosis using MATLAB simulations for fault categorisation. Power systems depend on transformers, which can cause major financial losses and operational disruptions. Infrequent and unpredictable fault events and power grid monitoring operating limitations make it challenging to collect real-world transformer failures for data-driven research. Synthetic fault situations are created in MATLAB to simulate real-world conditions. Inter-winding, L-L, and L-G faults—common transformer failures—are emulated. These failure scenarios are simulated to create a diverse and well-annotated dataset that ensures machine learning models generalise across operating systems. Voltage, current, active and reactive power, and frequency are used to classify faults in the dataset. However, transformer failure signals are transitory and non-stationary, making Fourier-based analysis ineffective for fault-related distortion detection. Wavelet Transform (WT) is the fundamental feature extraction method for time-frequency domain analysis. Wavelet transform allows localised time-frequency breakdown, making it ideal for fault-specific signal features. Fourier analysis only represents frequency domain. Spectral entropy, peak values, statistical moments (mean, variance, skewness), and harmonic amplitudes provide a complete picture of fault features, improving classification accuracy.

Figure 1. Workflow of the proposed framework

To determine the best fault classification method, SVM, Fine K-Nearest Neighbours (KNN), Linear Discriminant Analysis, and Decision Tree (DT) are tested. SVM handles high-dimensional data well, KNN handles non-linear patterns well, and Decision Tree is interpretable. To ensure effective fault categorisation, these models are trained and assessed using accuracy, precision, confusion matrix, and score. MATLAB simulations are used to classify faults in this research, ignoring real-time deployment, edge computing, and cloud monitoring. The goal is to design a robust classification framework that accurately classifies fault types using retrieved data. This study could be improved by using deep learning models like Convolutional Neural Networks (CNNs) or hybrid machine learning methods that combine feature-based techniques with deep learning to improve classification accuracy. Adding real-world transformer data and real-time monitoring methods could make this research more useful for predictive maintenance and condition-based monitoring in power systems.

III. Linear Discriminant Analysis

R. Fisher initially proposed linear discriminant analysis (LDA), a fundamental data analysis method, for differentiating between various flower species. The core principle involves identifying a lower-dimensional subspace, relative to the original data dimensionality, where the data points from the original problem are effectively separable. Separability is defined using statistical measures of variance and mean. Advantages of LDA include the solution via a generalized eigenvalue problem, enabling efficient processing of large datasets. Furthermore, kernel methods allow for the extension of LDA to non-linear scenarios [9]. While originally formulated for binary classification, multi-class extensions have also been developed. This discussion will address both, commencing with the simpler two-class case.

Let x1,... , xp ∈ R^m be a set of p data samples belonging to two different class sets, A and B. For each class we can define the sample means:

$$\bar{x}_A = \frac{1}{N_A}\sum_{x \in A} x, \bar{x}_B = \frac{1}{N_B}\sum_{X \in B} X \quad (1)$$

Given NA and NB as the sample sizes for groups A and B, respectively, we define the positive semidefinite scatter matrices as follows:

$$S_A = \sum_{X \in A}(X - \bar{x}_A)(X - \bar{x}_A)^T, S_B = \sum_{X \in B}(X - \bar{x}_B) \quad (2)$$

Each matrix represents the within-class scatter. Our objective is to identify a hyperplane, defined by the vector w, such that projecting the data samples onto this hyperplane minimizes their variance. This can be formulated as:

$$\min_{\phi}(\phi^T S_A \phi + \phi^T S_B \phi) = \min_{\phi} \phi^T (S_A + S_B)\phi \quad (3)$$

By definition, S = SA + SB. Conversely, the inter-class scatter matrix is defined as follows:

$$S_{AB} = (\bar{x}_A - \bar{x}_B)(\bar{x}_A - \bar{x}_B)^T \quad (4)$$

Following Fisher's discriminant analysis methodology, our objective is to identify an optimal hyperplane that maximizes the distance between class means while simultaneously minimizing the within-class variance. This is achieved through the maximization of Fisher's criterion.

$$\max_{\phi} \mathrm{F}(\phi) = \max_{\phi} \frac{\phi^T S_{AB} \phi}{\phi^T S_{\phi}} \quad (5)$$

IV. Results And Discussion

All the calculation and model training are performed using MATLAB 2024a on an 11th generation i7 computer having a computational speed of 3 GHz. After extracting all the features, condition indicators were added based on the dataset description. The whole data is then split into two parts: 70% of the data is kept for training the model and 30% of the data is kept for validation purposes. The efficiencies of successfully trained models are shown in Table I.

TABLE I. COMPARISON OF CLASSIFICATION ACCURACY

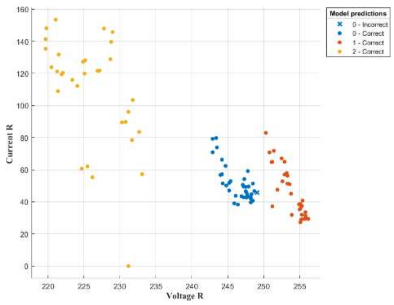
Algorithm	Accuracy Score (%)
Logistic Regression with Kernel	97.6%
Fine KNN	98.5%
Linear SVM	99.1%
Decision Tree	99.2%
Linear Discriminant Analysis	100%

The Logistic Regression with Kernel (LRK) model had 97.6% classification accuracy. Of 103 predictions, 100 were properly classified and 3 were misclassified. The confusion matrix shows class predictions' whole distribution:

Class 0 (Healthy Condition): 35 correct guesses, 1 incorrect Class 1.

Faulty Condition: 32 accurate forecasts, 1 incorrectly classified as Class 0.

32 right Class 2 predictions, 1 wrong Class 1 forecast.



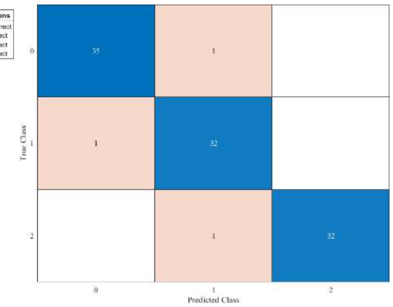
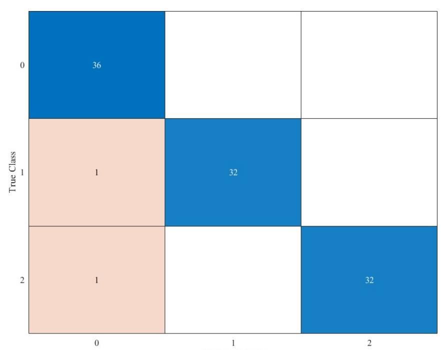


Figure 2. Scatter Plot of data points: Current R vs Voltage R   Figure 3. LRK Confusion Matrix

Very precise, the Fine KNN model achieved 98.5% classification accuracy. Out of 103 projections, 101 were correct and 2 were incorrect. The improved accuracy shows that the Fine KNN algorithm manages complex class boundaries well. However, the few misclassifications suggest that careful neighbour selection and distance measurements are needed to improve performance. Using Linear Support Vector Machines (SVM), the model had 99.1% classification accuracy. Out of 103 forecasts, 101 were correct and 1 was incorrect. SVM algorithm durability for the dataset is shown by its high accuracy. The model's single misclassification shows its limitations in handling edge circumstances or class overlap. These small issues suggest refining or investigating other kernel functions to improve model performance. With 99.2% classification accuracy, the Decision Tree model performed well. One forecast was misclassified, but 102 were correctly classified. Linear Discriminant Analysis gave the LDA model 100% classification accuracy. None of the 103 predictions were misclassified. This shows how well the LDA algorithm finds linear combinations of characteristics that best distinguish classes. The model's perfect accuracy suggests that the classification features are well-organised and linearly separable, making LDA ideal for this dataset. Linear Discriminant Analysis excels at transformer detection and classification. The results demonstrate its accuracy, reliability, and interpretability, making it a powerful tool for electrical engineering and fault diagnostics.



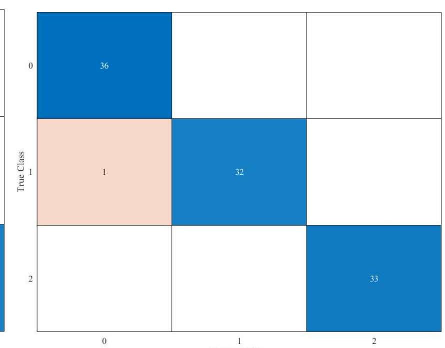


Figure 4. Fine KNN Confusion Matrix   Figure 5. Linear SVM Confusion Matrix

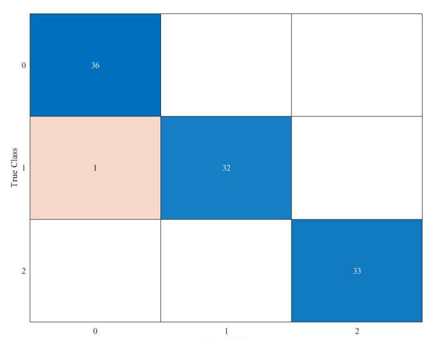


Figure 6. Decision Tree Confusion Matrix

V. CONCLUSION

This paper presents a framework through which transformers' operating conditions can be effectively classified into healthy or faulty. The current and voltage value of the transformer are used to extract important features through wavelet transform. The extracted features are then used to train a no of machine learning algorithms. A total of 5 algorithms have been assessed for the considered problem. Among them, LDA algorithm came out to be best performing with 100% accuracy in fault classification. In future, the authors will utilise time-frequency features to train a deep learning network, which may pave alternate ways in this domain.

REFERENCES

[1] K. Premalatha, R. Janaranjani, S. Bhuvaneswari and M. Karthik, "Transformer Fault Identification and Classification of Using Machine Learning," 2024 2nd International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS), Erode, India, 2024

[2] A. Vyshnavi, M. P. Mali, S. Hemelatha, M. Gupta, M. Sindhu and A. Singla, "Wavelet Transform Based Feature Extraction for Fault Diagnosis in Machinery," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024

[3] H. Ma, H. Song, C. Meng and R. Wang, "Fault Diagnosis of Power Transformer Based on Improved Neural Network," 2024 5th International Conference on Computer Engineering and Application (ICCEA), Hangzhou, China, 2024

[4] A. Balan, S. T. L, M. P. V and K. Deepa, "Detection and Analysis of Faults in Transformer using Machine Learning," 2023 International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT), Bengaluru, India, 2023

[5] H. Hadiki, F. S. Hasnaoui and S. Georges, "Transformers Faults Prediction Using Machine Learning Approach," 2023 Fifth International Conference on Advances in Computational Tools for Engineering Applications (ACTEA), Zouk Mosbeh, Lebanon, 2023

[6] T. -H. Han, S. -C. Ko and S. -H. Lim, "Analysis on Three-Phase Ground Fault Current Limiting Operations of Three-Phase Transformer Type SFCL Using Two Superconducting Modules," in IEEE Transactions on Applied Superconductivity, vol. 32, no. 6, pp. 1-7, Sept. 2022

[7] Y. Zhuo and Z. Ge, "Auxiliary Information-Guided Industrial Data Augmentation for AnyShot Fault Learning and Diagnosis," in IEEE Transactions on Industrial Informatics, vol. 17, no. 11, pp. 7535-7545, Nov. 2021

[8] J. H. Estrada, S. V. Ramı´rez, C. L. Cortés and E. A. C. Plata, "Magnetic Flux Entropy as Tool to Predict Transformer's Failures," in IEEE Transactions on Magnetics, vol. 49, no. 8, pp. 4729-4732, Aug. 201

[9] P. Xanthopoulos et al., Robust Data Mining, SpringerBriefs in Optimization, DOI 10.1007/978-1-4419-9878-1 4, © Petros Xanthopoulos, Panos M. Pardalos, Theodore B. Trafalis 2013