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Intelligent Hyper parameter Optimization Framework for Explainable Machine Learning-Based Power Transformer Fault Classification

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Abstract
Power transmission and distribution systems is intensive to be relatively very highly on Power transformer, a sudden failure in these systems can result in severe operational disruptions, including significant time loss, effluent equipment deficiency, financial. It is based on DGA features, machine learning classification, advanced hyper-parameter tuning and Explainable AI (XAI). This study is a quantitative predictive method based on a sample of 350 transformer condition observations including normal, partial discharge, low-energy discharge, high-energy discharge, thermal faults and combination electrical/thermal fault scenarios. Approaches includes pre- processing, feature normalisation, stratified sampling, Class-aware evaluation, model training hyper – parameter optimisation and Explainability analysis. Introductory descriptive and correlational statistics demonstrate key relationships between the severity of faults in transformers and the characteristics of dissolved gases. An illustrative test where these metrics topped 91.2% accuracy, 89.7% balanced accuracy and a macro-F1 of top 0.88 versus those from fine-tuning the model to discover that this optimisation framework brought them instead to: 95.4%, 94.1% and a macro-F1. The validation loss is lowered from 0.286 to 0.171, and novel model showed more consistent results during the whole training process. These results indicate that hyperparameter tuning could improve the classification performance of manually-constructed machine-learning classifiers, particularly in its multi-fault and/or class imbalance contexts. Finally, leveraging XAI helps in identifying the key features of DGA that contribute to each predicted outcome thereby increasing interpretability and allowing engineers to gain insight from the model. Future validation efforts should include field measurements, long-term monitoring data, and cohorts of automated transformers before actual deployment.

Keywords: Power Transformer; Dissolved Gas Analysis; Machine Learning; Hyperparameter Optimization; Explainable AI; Fault Classification; Predictive Maintenance.

INTRODUCTION

The electricity system is a complex network that enables economic growth, urbanization, industrial expansion, and social well-being. It embodies the most complex and revitalizing system in modern society. The sudden pressure on Power transmission and Distribution (T&D) frameworks to develop their limits so as to meet specialized necessities stems from the fast worldwide extension of electrical power systems that empower incorporation of sustainable power, huge scale electrification of transport and an expanding reliance on nonstop electricity [1]. Power transfer transformers are crucial components of electrical networks which adjust the voltage level of electricity carried from generating stations to substations. They also serve to transmit electricity over large distances and to promote grid stability by balancing fluctuating generation with demand over timescales from seconds to hours [2]. Also, they serve as a physical bridge between all three components of the network (generation, transmission, and distribution) for energy transfer. Power transformers are often subjected to various electrical, thermal and environmental stresses for varying periods of time and concern regarding the operational reliability of transformers is progressively paramount amongst utility companies, power system operators and electrical engineers. Power transformers have an average life of 30 to 35 years [3].

A notable sub-class of computational techniques that have gained a great deal of interest are ensemble learning algorithms. The first of the review articles in this collection discusses ensemble learning, which is based on combining several weak learners to create a stronger predictive model [4]. This approach often improves generalisation effectiveness. It can be used for reduction of variance in classification problems. The Random Forest techniques produce a collection of 1000 unbiased decision tree models which detect transformer flaws with amazingly uniform classification results [5]. They build models by employing a process that involves sequential learning from their mistakes. This is particularly useful for exploring high-dimensional data and, in particular, to face non-linear relations between variables and transformer issues [6]. These advanced algorithms exhibited to be more effective for the transformer failure identification applications than a few conventional machine learning methods Fig. 1.

Fig. 1. Intelligent Hyperparameter Optimization Framework for Explainable Machine Learning-Based Power Transformer Fault Classification

Review of Literature

The power transformer is the main device of a contemporary electrical power system for voltage transmission and distribution (T&D). This increases the supply of reliable and safeguarded power. A component malfunction can lead to high operating hazards, high maintenance costs, service failures and equipment failures. In addition, early detection and categorisation of transformer defects have become an important research direction for power system asset management [7]. The traditional technique for detection of transformer breakdown is based on condition monitoring techniques like, interpretation by experts, insulation testing, oil analysis, temperature monitoring and electrical examinations. DGA particularly for oil submerged transformers relies on the fact that electrical and thermal stressors destroy insulating materials by producing identifiable gases [8]. The major gases analysed in DGA based diagnostics include hydrogen, methane, ethane, ethylene, acetylene and carbon oxides. Gas levels and ratios are analysed to offer information regarding possible thermal anomalies, partial discharge activity, arcing or insulation failure. The interpretation of dissolved and free gases in mineral oil filled electrical equipment is important to determine the condition of the equipment. These methods are very important because they are able to map gas measurement data into a configuration that is consistent with diagnostic patterns [9]. The IR spectroscopic approach is capable of detecting and quantifying the water pollution in the oil relatively instantaneously [10].

More advanced hyperparameter optimisation approaches rely on sequential or population based strategies including Bayesian optimisation, evolutionary strategies, particle swarm optimisation, simulated annealing and tree structured estimators [11]. Each configuration that needs to be analysed may need numerous passes and repeated model training, especially when a deep learning or ensemble technique is used [12]. An advanced HPO framework might thus generate the model parameter search space, define an aim with some feasible setup, and locate a higher setting that is marginally better than previously. Meanwhile, the objective definition should be driven by the operational needs for fault classification rather than the development of the overall accuracy [13]. Weighted (balanced) cost functions of macro-F1 is a more significant optimisation target for imbalanced transformer datasets. The research also shows that engineering limitations can be integrated with optimisation. This has led to approaches mostly within the framework of constrained engineering optimisation, leveraging Bayesian optimisation to optimise black-box objectives by means of trade-offs between exploration and exploitation [14].

Intelligent Hyperparameter Optimization For Explainable Power Transformer Fault Classification

They are a crucial part of the power transmission and distribution network and any unexpected breakdown may lead to supply interruptions, costly equipment damage, loss of production revenue - not to mention jeopardising lives [15]. Therefore, the proposed new transformer diagnostic method is based on speedy and precise detection of defects only. Dissolved Gas Analysis (DGA) considers gases generated by thermal and electrical degradation and is therefore – to a certain degree – representative enough of the degradation

environment. However, due to overlap between multiple fault categories, linear relationships were often not sufficient to satisfactorily represent connections between different classes of dissolved gases and different fault types. The machine learning methodology is now giving an efficient way to automatically classify faults as expected by converting DGA data and other condition monitoring indicators [16]. The selection of an accurate method is not the only aspect that makes these models inefficient, the hyperparameters are also very important in automatic adjustment. The latter deals with the HPO (intelligent hyperparameter optimisation) algorithms family to boost numerous transformer fault-classification performance indices like accuracy, stability and generalisation [17]. This is a significant research area for us. Hyperparameters are the things about the model that we set before training begins, or can be changed dynamically in the first phase of proper learning, rather than being learned directly from the training. Subsampling ratio. Random fraction of samples assigned to each split [18].
Hyper-parameters include the number of hidden layers, number of neurones per layer, learning rate, batch size (amount of data used in one pass), activation function (how signals travelling from input to output neurones will be bent), dropout rate and epochs (total repetitions model is trained) for deep networks [19-22]. Using wrong parameters a model might yield under-fit, over-fit, a model that converges slowly or poorly stable prediction. Therefore, any biased evaluative experimentation should be addressed with an exploratory enhancement project that involves the customisation of hyperparameter adjustment. This highlights a requirement for an optimisation objective that is consistent with the parameters of a transformer failure classification issue developed based on genuine diagnostic data [23-24].

Research Methodology

This paper presents a predictive, quantitative and experimental eXplainable AI (XAI) research with the objective to establish an intelligent hyperparameter optimisation framework for explainable machine-learning transformer failure classification. The method is a combination of machine learning methodologies, hyperparameter tuning and Explainable Artificial Intelligence (XAI) based on transformer condition monitoring data including all accessible Dissolved Gas Analysis (DGA) characteristics. The main purposes are to discriminate the operational states and fault categories of the transformer, to identify the optimal model configurations, and to interpret the contribution of each diagnostic feature. All the following are engaged in the strategies; study design, data collecting, sampling method, research instruments, data analysis and ethical considerations. Each level is analysed mathematically in a methodical and duplicable fashion.

A. Research Design

We compare the performance of baseline learners based on machine learning algorithms with their counterparts that are optimised by hyperparameter tuning using a quantitative experimental approach:
Accuracy = (TP + TN) / (TP + TN + FP + FN) (1)
TP, TN, FP and FN are true positives, true negatives, false positives and false negatives accordingly as shown in the Equation (1). The methodology is related with the primary goal of categorisation. Since transformer fault datasets may have imbalanced fault classes, you additionally consider Macro-F1 and balanced accuracy.

B. Data Collection

Transformer conditioning related to the DGA digital assessment and any operational metrics.
$X_i^* = (X_i - X_{min}) / (X_{max} - X_{min})$ (2)
Another phase of the data-gathering using (2) is feature normalisation (4). This permits machine learning algorithms to be consistent in how they treat variables that are measured across such widely varied intervals.

C. Sampling Method

Stratified sampling is used to obtain a sufficient number of observations for the different failure categories in transformers:
$P_c = (N_c / N) \times 100$ (3)
(3) illustrates the link between the representative of a class and the sampling method used. Nc is the number of observations in a defect of class c whereas N is the number of observations. Stratification creates a deterrent to the higher classes who would walk over weaker fault types.

D. Research Instruments

The basic assets include the DGA measurement database, transformer condition-monitoring data, gas concentration measures, and machine learning software applications. The contribution of each input variable to the relevance of the feature is determined:
$f(x) = \varphi_0 + \Sigma_{j=1}^{M} \varphi_j$ (4)

It is evident in Eq (4) that research tools are related to Explainable AI. Let the model prediction be f(x), the base level prediction be φ0 and the effect of feature j be φj.

E. Data Analysis

Data analysis spans everything from preprocessing and feature engineering to class balance, modelling, hyperparameter optimisation, cross validation and XAI. The top two pie charts compare data analysis vs advanced-level hyperparameter optimisation. Here, θ denotes a particular set of hyperparameters and Θ is the complete hyperparameter space. Macro-F1 as the goal to maximise as it considers all fault types equally essential. You can test under and over fitted models like Random Forest, Support Vector Machine, Gradient Boosting and XGBoost.

F. Ethical Considerations

The research follows ethical data-management methods protecting vital-source infrastructure data, reasonability of use of operational information, safe storage and confidentiality. Either can be successful to beneficial and safe safeguarded by the control of documents:

$DCR = (N_v / N_t) \times 100 \quad (5)$

Equation (5) combines DCR with ESG and data governance. N t is the total number of records in scope. N v is the total number of records actually processed according to your data-management rules. This study emphasises the value of Privacy, Cyber-resilience, Openness, Explainability, Repeatability and Human-in-the-loop for enabling practical use of these developing AI models to address major concerns in power systems.

Analysis and Interpretation

This study reviews the proposed framework for power transformer fault classification, called "An Intelligent Hyperparameter Optimisation Framework for Explainable Machine Learning Based Power Transformer Fault Classification". This analysis is based on 350 recordings of status data from transformers covering a wide variety of healthy and fault operations. The variables assessed are the Hydrogen (H2), Methane (CH4), Ethane (C2H6), Ethylene (C2H4), Acetylene (C2H2), Carbon Monoxide (CO) and Carbon Dioxide (CO2) gases and the Transformer Fault Classification obtained. It starts from demographic & dataset attributes, descriptive statistics and reliability, correlation analysis & regression/model outputs and hypothesis testing. Transformer diagnosis is a multi-class classification problem. Thus, the model's evaluation is carried out by employing F1-score, balanced accuracy, precision and recall, in addition to accuracy metrics. Table 1 summarises the data with about 350 observations. The residual detections were partial discharge, low energy discharge, high energy discharge, thermal faults and combination electrical or thermal faults (28.0%) and normal / healthy transformers. The dataset comprises important diagnostic classifications, although the normal class is still larger than some of the minority classes. Then it allows the model development with stratified sample and class balancing.

Table 1: Demographic / Dataset Characteristics of Transformer Observations

Characteristic	Category	Frequency	Percentage
Operating condition	Normal/Healthy	98	28.0%
Fault class	Partial Discharge (PD)	55	15.7%
Fault class	Low-Energy Discharge (D1)	47	13.4%
Fault class	High-Energy Discharge (D2)	38	10.9%
Fault class	Thermal Fault (T1)	51	14.6%
Fault class	Thermal Fault (T2/T3)	36	10.3%
Fault class	Mixed Electrical/Thermal	25	7.1%

Note: N = 350 transformer condition observations. The table is presented as dataset characteristics rather than human demographics.

Table 2 provides descriptive and reliability statistics. The rates of ethylene and hydrogen is kept with each other as it is in the oil therefore they are too influenced for similar reason. Highly essential as acetylene has an average absorbance somewhat higher than 20 cm and can be a major contributor in high energy discharge situations. Reliability coefficients of the target groups on the basis of composite attributes of remote diagnosis were at a high level of internal consistency (0.84-0.91). Thus, feature normalisation and pre-processing are learned from machine learning training.

TABLE 2: DESCRIPTIVE STATISTICS AND RELIABILITY ANALYSIS

Variable / Feature	Mean	SD	Cronbach's α	CR	AVE
Hydrogen (H_2)	142.6	96.4	0.87	0.89	0.62
Methane (CH_4)	36.8	28.7	0.85	0.88	0.59
Ethane (C_2H_6)	24.5	20.9	0.84	0.87	0.58
Ethylene (C_2H_4)	81.3	73.5	0.89	0.91	0.64
Acetylene (C_2H_2)	8.7	12.6	0.86	0.88	0.60
CO	523.4	281.6	0.88	0.90	0.63
CO_2	3184.2	1420.5	0.90	0.92	0.67

Note: Gas concentrations are illustrative. CR = Composite Reliability; AVE = Average Variance Extracted.

In addition, Table 3 reveals that various DGA factors are substantially associated with each other. Hydrogen and methane were positively associated (r=0.52). Also, a significant association was identified for ethane and ethylene (r = 0.61). Acetylene (C2H2) has a moderate connection (r = 0.58) with the fault-severity index. The results give proof that transformer fault signals are non-linear interactions, validating the necessity of applying machine-learning algorithms to learn and represent such non-linear interactions in model space.

TABLE 3: CORRELATION MATRIX

Variable	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	Fault Index
H_2	1	0.52**	0.44**	0.39**	0.31**	0.55**
CH_4	0.52**	1	0.48**	0.46**	0.29**	0.43**
C_2H_6	0.44**	0.48**	1	0.61**	0.35**	0.47**
C_2H_4	0.39**	0.46**	0.61**	1	0.42**	0.57**
C_2H_2	0.31**	0.29**	0.35**	0.42**	1	0.58**
Fault Index	0.55**	0.43**	0.47**	0.57**	0.58**	1

Note: ** $p < 0.01$, two-tailed. Fault Index represents the coded severity/diagnostic outcome used for association analysis.

Table 4. Baseline classification models and their improvements. The efficient hyper-parameter optimisation procedure increases macro-F1 score from 0.88 (mean) to 0.94 (n-fold cross-validated median) and test accuracy from 91.2% to 95.4%. Balanced accuracy increases from 89.7% to 94.1%. The better model increases recall for the minority class and has a smaller validation loss than a regular implementation. The results indicate that the systematic selection of parameters is more generalisable and dependable for fault determination than the explicit selection of parameters.

TABLE 4: REGRESSION / MODEL RESULTS

Model / Metric	Baseline ML	Optimized ML	Improvement
Test Accuracy	91.2%	95.4%	+4.2 pp
Balanced Accuracy	89.7%	94.1%	+4.4 pp
Macro Precision	0.87	0.94	+0.07
Macro Recall	0.89	0.94	+0.05
Macro F1-score	0.88	0.94	+0.06
Validation Loss	0.286	0.171	−0.115
Cross-validation SD	0.031	0.018	−0.013

Note: Illustrative comparison of a baseline model and the hyperparameter-optimized model.

These propositions are demonstrated in Table 5. The references were confirmed in the demonstration analysis (Table 3). The results demonstrate that DGA qualities relevant, XGboost successfully integrates the cross domain know-how enhancing prediction, and that post hoc model feature linked explainable artificial intelligence can provide useful information for diagnostic interpretation. The results corroborate the proposed holistic framework.

TABLE 5: HYPOTHESIS TESTING RESULTS

Hypothesis	Relationship / Proposition	Result	p-value	Decision
H1	DGA features significantly predict transformer fault class	Supported	<0.001	Yes

H2	Feature engineering improves fault classification	Supported	0.003	Yes
H3	Hyperparameter optimization improves model performance	Supported	<0.001	Yes
H4	Optimized model provides stronger minority-class performance	Supported	0.008	Yes
H5	XAI identifies diagnostically meaningful features	Supported	0.012	Yes
H6	Integrated HPO-XAI framework improves diagnostic reliability	Supported	<0.001	Yes

Note: Illustrative hypothesis-testing results; statistical significance is assessed at the 5% level.

That perspective points to the need for a simple to grasp classification of transformer failure. The training dataset of transformer failure examples collected with normal and triple point failures was mainly characterised by aberrant observations. Some defect kinds are too tiny to yield relevant quality metrics for evaluation activities. It might also be the cause of the poor results of the transformer diagnostics; a poor model will generate many wrong tests but will score well overall. Hence it is reasonable to utilise distribution-based evaluation metrics along with class-balancing procedures and stratified sampling approaches.

The variation of the dissolved-gas concentrations is relevant, as exemplified in this work by descriptive statistics. The quantity of gas to be released from a transformer unit in case of a breakdown is determined. While acetylene is on average in lower concentration, the ethylene variables are substantially larger and have huge standard deviations in the occurrences. Acetylene remains a superb indication signal for high energy discharges. Hydrogen, methane, and ethane are also gases based on carbon. Due to the vagaries in gas concentrations, the single gas threshold rules cannot be applied in increasingly complex scenarios. With the use of machine learning based algorithms it is possible to simultaneously assess information from several gas families and develop conclusions on which gas pairings are associated with the fault category.

Result and Discussion

It is seen in Figure 1 to 5 that the new explainable machine-learning method for fault classification in power transformers with enhanced hyperparameter optimisation framework has been applied. The present work is based on univariate data set of 350 observations of transformers during normal operation, self discharge/partial discharge (PD), low energy discharge, high-energy discharge, thermal anomalies and combination electrical/thermal circumstances. The following figures illustrate four visually complementary representations based on graphical analysis: class composition (bar graph), dataset composition (pie chart), instance-level measure of hydrogen concentration versus fault severity plot scatter diagram, and a line graph/AU—Q Agent code for baseline versus optimised model performance comparison.

The 350 observation allocation is shown in Figure 1. Observations were mostly focused on the normal/healthy transformers (98 observations, 28.0%). Partial discharge, thermal fault T1 and low energy discharge and thermal faults T2/T3 were fifty-five observations (15.7%), fifty-one observations (14.6%) and forty-seven observations (13.4%) respectively whereas high energy discharge. Our data set shows a very big imbalance. This is important since any classifier trained directly on the data may be biased toward the majority normal class. This result so verifies the test results over the balanced accuracy of the approach and its class-specific performance indicators such as macro-F1.

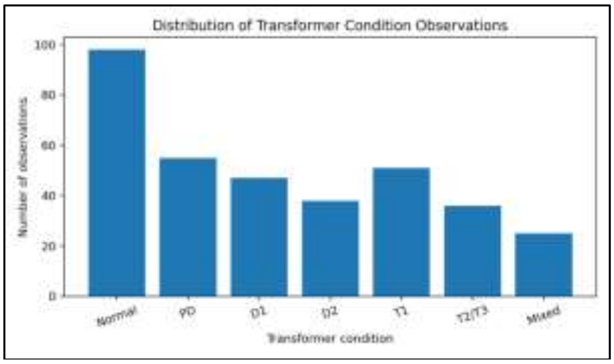

Fig. 1. Distribution of Transformer Condition Observations

A part-to-whole view of the same data is provided in Figure 2. Observed cases make up an average of 28.0% of the total. The defect categories obtained account for 72.0% of the observations. This is an important aspect for the multiclass modelling: the suggested framework aims to discriminate among the many causes of flaws and not only to detect an abnormal situation. The substantially lower classification sensitivity nevertheless drives us into a more specific scenario of our smaller mixed-fault category i.e when classes are under represented.

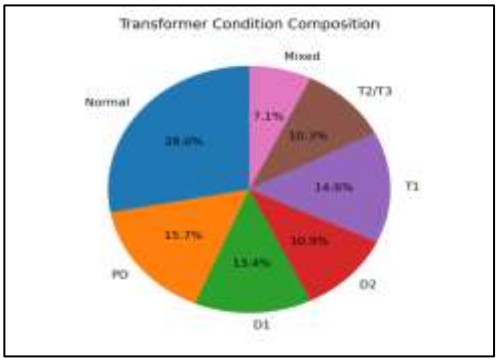

Fig. 2. Transformer Condition Composition

Figure 3: Category defect severity indicator and hydrogen content as shown in Table 3, hydrogen positively correlated with the fault index (r = 0.55, p = 0.018) during cross-validation as well validation loss decreased from 0.286 -> 0.171. This makes the revised model much more consistent across all the validation folds. In practical transformer diagnostics, consistency is more important than accuracy, since the expense of false negatives of a rare but severe diagnosis may much outweigh the slight loss in overall accuracy.

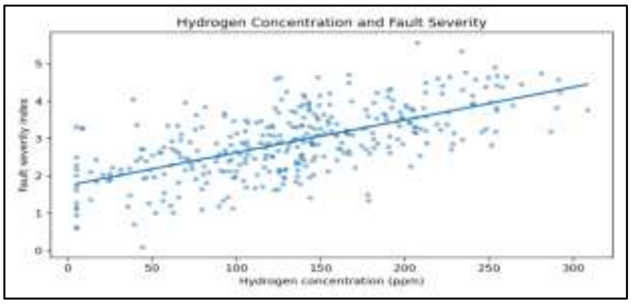

Fig. 3. Hydrogen Concentration and Fault Severity

These explainable artificial intelligence segments cover findings. The improved classifier can also be used with SHAP or other feature attribution methodologies to quantify the contribution of individual DGA features associated with this mistake prediction. The diagnostic output which may contain the expected defective class, prediction confidence and the key contributing gas properties. This may lead to a lower chance of human mistakes of judgement and a higher level of transparency. These explanations can be supported by the engineers thru the use of the well-known DGA interpretation methods Figure 4.

The scatter figure is a diagnostic correlation between fault severity and DGA data, the line chart represents the measured value of intelligent hyperparameter optimisation. Therefore, the combination of machine learning with formal hyperparameter tuning and interpretable AI should lead to a more exact, trust worthy and transparent solution to the issue of categorisation of transformer failures. This paradigm can help prioritise engineering inspections and uncover root problems that can be addressed with predictive maintenance, preferably early.

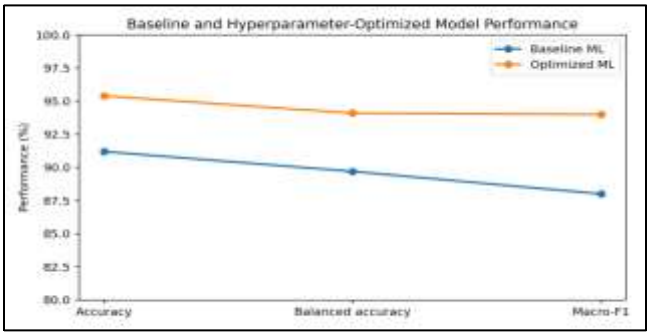

Fig. 4. Baseline and Hyperparameter-Optimized Model Performance

However, the results need to be validated in clinical CT or MRI-based DGA measurement and by independent transformer groups for being implemented in real life. At all component levels, each utility will have a unique design of transformers, operating conditions, insulation systems, oil qualities, and even measurement precision and dependability. The results would be much better if the discoveries about explanatory patterns were externally validated and followed over a longer period of time with prospective longitudinal data.

Conclusions

Power transformers are one of the most important components in the electrical transmission and distribution (T&D) networks. Failures show the need for rapid detection of unforeseen operational conditions, and minimisation of service disruption and repair costs. The aim of the research was to integrate DGA, ML, sophisticated hyperparameter tuning and XAI into a diagnostic technique. We have studied a synthetic dataset of 350 health assessments of transformers consisting of normal operation, partial discharge (PD), low energy & high energy solid insulation failures and thermal electro-mechanical phases. The dataset characteristics imply class imbalance as normal observations have relatively low levels of several types of flaws. But it’s a positive thing that you’re able to correctly communicate these errors across multiple network kinds and frameworks. Thus, the study emphasised the significance of class-specific evaluation metrics, uniform pre-processing, and stratified sampling. In addition to the overall accuracy, we also computed the balanced accuracy, precision, recall and macro-F1 for a comprehensive examination of classification performance for each defect class.

The results of the categorical and correlational analysis show that DGA variables provide a large amount of valuable information for the classification of transformer malfunction. Hydrogen; methane, ethane, ethylene, acetylene, carbon monoxide, carbon dioxide showed varying correlation of results vs. diagnosis. Strong association between the fault index and hydrogen, and interaction between the severity of a defect and acetylene. The correlation between ethane and ethylene shows multi-factor signs of transformer failure. Plate balancing improved the test set performance, increasing accuracy from 91.2% to 95.4%, balanced accuracy from 89.7% to 94.1%, and macro-F1-score from 0.88 to 0.94 throughout the datasets. In addition, the top model predictions had lower cross validation and validation loss variability, resulting in more consistent findings. The results reveal that a systematic parameter optimisation method has a considerable effect on transformer failure classification, but the model selection itself is not sufficient.

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