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Detecting Incipient Faults in Transformers: A dual Cascade Decision Tree Approach Using DGA

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Abstract

The prompt diagnosis of abnormalities in power transformers is of paramount importance. Dissolved Gas Analysis (DGA) serves as an essential and vital tool for identifying faults. This paper introduces a method based on a decision tree (DT) algorithm using DGA to assess the condition of transformer oil samples in two steps: Normal/Faulty and Fault Type. The DTs in this paper were trained using 80% of the 729-sample dataset and evaluated with the remaining 20%. The dataset includes concentrations of five gases dissolved in transformer mineral oil: H2, CH4, C2H2, C2H4, and C2H6. These key features**,** along with other necessary parameters for learning DTs, contribute to the analysis; by employing two separate and sequential DTs for diagnosing transformer oil samples, the proposed method significantly improves the accuracy of identifying the health status and the type of potential fault. In the test samples, the method achieved a precision of 95.5% for normal state detection and 78.3% for fault type identification.

Keywords: power transformer, dissolved gas analysis, decision tree.
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1. Introduction

Power transformers play a crucial role in ensuring the uninterrupted supply of electricity and are among the most significant components in power networks. However, they are also among the costliest elements. Replacing them in the event of malfunctions can be a costly and labor-intensive process. Consequently, it becomes imperative to diligently monitor and assess the condition of power transformers. These devices produce combustible gases in minimal concentrations during regular operation. The quantity of these gases is directly linked to the duration of usage and is associated with the inherent degradation of both cellulose and the transformer oil [1]. In the event of a fault within the transformer, the insulators are subjected to both electrical and thermal stresses; these stresses lead to the chemical breakdown of insulation in oil-filled transformers. As a result of this chemical decomposition, gases are produced, and these gases can be dissolved in the transformer oil. Research conducted in recent decades has substantiated a close correlation between the dissolved gases in transformer oil and the nature of faults. Consequently, the type of fault occurring in the transformer can be identified by analysing the quantity and type of gases generated [2].

Various approaches have been developed for interpreting Dissolved Gas Analysis (DGA), encompassing both conventional and computational intelligent methods. Conventional methods such as the Key gas method introduced in [3], Dornenburg ratio [4], and Rogers ratio [5] rely on assessing the concentration and ratio of dissolved gases. Additionally, graphical methods such as Duval triangle 1 [6], Duval pentagon 1 [7] have been introduced, demonstrating their superior accuracy. In recent times, computational intelligence methods have gained increased attention due to significant advancements in processor speed and computer memory capacity. Artificial Intelligence (AI) classification techniques, including artificial neural networks [8, 9], fuzzy logic [10], support vector machines with k-nearest neighbors [11], DT [1], and random forest [12], have been employed. While new methods based on artificial intelligence often enhance diagnosis accuracy, they are frequently challenging to comprehend and lack interpretability for fault detection. Moreover, many of these methods do not account for diagnosing the health status of the transformer .Therefore, it is important to provide an intelligent method that covers these disadvantages of new methods and at the same time has high interpretability.

The aim of the present paper is to propose a new method based on computational intelligence for detecting incipient faults in transformers through dissolved gas analysis. The main difference between this study and previous research is the simplicity of detecting the normal or faulty status of samples. Finally, the performance of the proposed method will be compared with conventional methods. In the following, the importance of DGA, the structure of the DT algorithm, and its application in fault detection are discussed in Section II. The statistical results of the new method are presented in Section III, and the paper concludes in Section IV.

2. Methodology

The DGA test is important because it informs transformer specialists about the occurrence of critical conditions. In fact, before the Buchholz relay warns and the amount of gas caused by the mineral oil in the transformers reaches a high limit, performing this test allows for checking the condition of the transformer immersed in oil and diagnosing potential faults. In this paper, due to the positive impact of artificial intelligence algorithms, the DT algorithm has been employed for fault detection. The methodology of this paper is visually represented in the flowchart provided in Figure 1.

A) Decision Tree

DTs are predictive models within supervised learning, valued not only for their undeniable utility across a broad spectrum of applications but also for their robustness; single DTs are characterized by their high interpretability. The entire model can be accurately represented through a straightforward two-dimensional graphic, specifically a binary tree. This binary tree visualization makes it easy to comprehend and interpret the decision-making process of the algorithm [13]. For this reason, in this paper, single DTs have been used to diagnose the condition of transformer oil samples.

To build a DT, various settings should be considered. Here are three of the most important features:

- Feature selection: The selection of features from the dataset is a crucial setting for any machine learning algorithm.
- The depth of the tree: This determines how many levels and how deep the tree extends.
- The degree of impurity: To determine impurity, two criteria are used, which are explained below [13]:

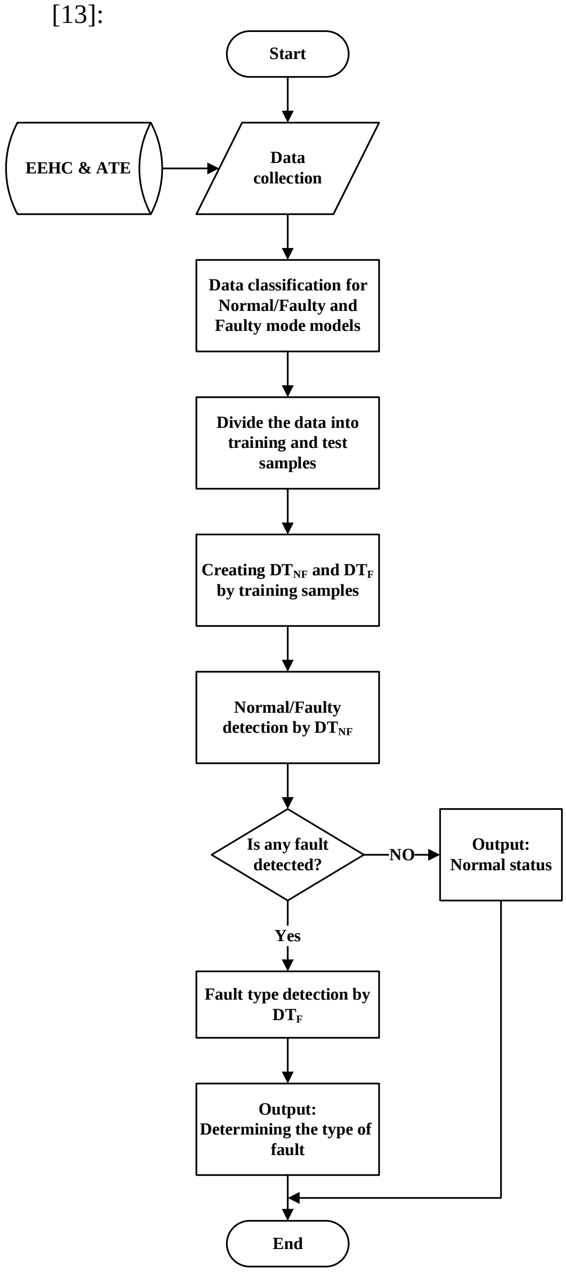

Fig. 1.Proposed method for detecting power transformer faults.

Gini index: $$\sum_{k \neq k'} p_{mk} \times p_{mk'} = \sum_{k=1}^{K} p_{mk} (1 - p_{mk}) \quad (1)$$

Entropy: $$-\sum_{k=1}^{K} p_{mk} \times \log p_{mk} \quad (2)$$

Here, p_{mk} represents the proportion of samples belonging to node m (N_m) and class k, y_i is the class of sample, and it is defined as follows [13]:

$$p_{mk} = \frac{1}{N_m} \sum I (y_i = k) \quad (3)$$

B) Using DTs in fault diagnosis

In this article, two DTs are proposed. The first tree is used to diagnose the health of the transformer. Initially, the state of the sample is determined between two states: normal and faulty; in the next step, the second DT is employed. This tree comes into play when the first tree identifies the sample as faulty. The second DT is then used to diagnose the specific type of fault.

The primary features of the dataset include the concentrations of the five main gases measured in parts per million (ppm). However, additional features can be introduced; the simplest addition is the percentage of each of the five main gases, calculated based on equations 4 to 8.

$$H2\% = \frac{100\times[H2]}{[H2]+[CH4]+[C2H2]+[C2H4]+[C2H6]} \tag{4}$$

$$CH4\% = \frac{100\times[CH4]}{[H2]+[CH4]+[C2H2]+[C2H4]+[C2H6]} \tag{5}$$

$$C2H2\% = \frac{100\times[C2H2]}{[H2]+[CH4]+[C2H2]+[C2H4]+[C2H6]} \tag{6}$$

$$C2H4\% = \frac{100\times[C2H4]}{[H2]+[CH4]+[C2H2]+[C2H4]+[C2H6]} \tag{7}$$

$$C2H6\% = \frac{100\times[C2H6]}{[H2]+[CH4]+[C2H2]+[C2H4]+[C2H6]} \tag{8}$$

The next set of features involves gas ratios, as outlined in Table 1. The final feature is the sum of the concentrations of the five main gases, measured in ppm; Figure 2 shows these features.

To assess the performance of the models, two indicators, accuracy and recall, have been employed; these indicators are calculated according to equations 9 and 10.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{10}$$

In these relationships, *TP*, *TN*, *FP*, and *FN* represent true positive, true negative, false positive, and false negative, respectively.

Table.1.
Gas Ratios obtained from IEEE C57.104 [3].

R1	***R2***	***R3***	***R4***	***R5***	***R6***
$\frac{CH4}{H2}$	$\frac{C2H2}{C2H4}$	$\frac{C2H2}{CH4}$	$\frac{C2H6}{C2H2}$	$\frac{C2H4}{C2H6}$	$\frac{C2H6}{CH4}$

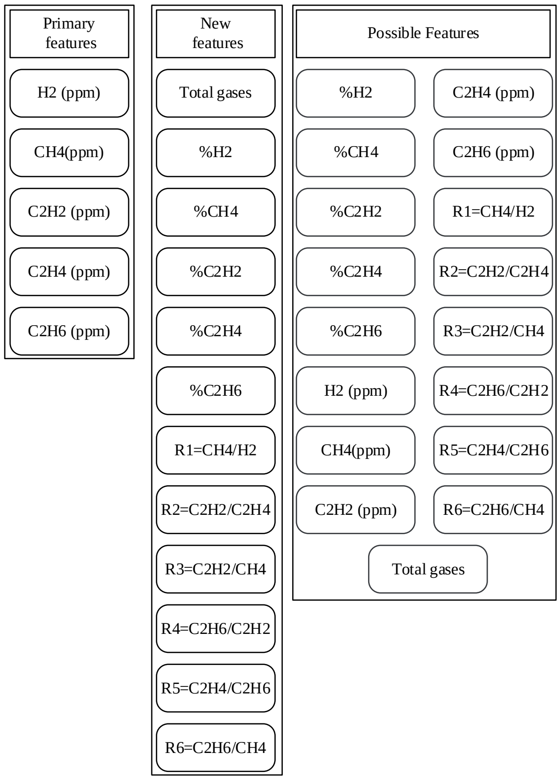

Fig. 2. Features extracted from gas chromatography experiment for DGA and creating DT.

3. Results and discussion

Diagnosing the health of the transformer is the first step in the DGA test. In [3, 15], conditions are considered for this, and the methods of Rogers ratio and Dornenburg ratio also address this case. In this paper, a DT is used to detect the health status of the oil samples.

To create DTNF (Normal/Faulty DT), first, it is necessary to divide the dataset samples into two categories: normal and faulty. We have 177 normal samples and 552 faulty samples. In the next step, training and testing samples should be specified. Here, 80% of the samples are designated as training data, and the remaining 20% are assigned as test data. DTs are then built using the training samples.

Figure 3 shows the effect of the maximum depth change on the accuracy score for a DTNF with Gini impurity criterion. The Accuracy Score calculated as below:

$$\text{Accuracy Score} = \frac{\sum_{i=1}^{n} N_i \times Accuracy_i}{\sum_{i=1}^{n} N_i} \tag{11}$$

Where, i is the class number, n is the count of classes, and Ni is the number of samples in class i.

Figure 4 shows the effect of the maximum depth change on the accuracy score for a DTNF with Entropy impurity criterion. According to Figures 3 and 4, the DT trained by the Entropy impurity criterion exhibits better performance in detecting the

Normal/Faulty status of the transformer. As the depth of a tree increases, the two-dimensional representation of the tree become larger, sometimes leading to overfitting. On the other hand, a machine learning model performs well when its performance is consistent between the training and testing data. Therefore, choosing a depth of 6 and the Entropy criterion is a suitable option for DTNF.

The second DT related to the Normal/Faulty status is represented in Figure 5. This tree contains 29 nodes. The rhombuses and rectangles are called nodes. Specifically, rhombuses are decision nodes, and rectangles are leaves of a DT. The green rectangles belong to the Normal class, and red rectangles belong to the Faulty class. The expression [a, b], present in all nodes, represents the number of [Normal, Faulty] samples. The first node, which contains the condition "Total < 52.5", serves as the root node of the tree.

In this DT, all the conditions are in the form of "<", representing "less than"; if this condition is met, the samples are directed to the left side of the decision node; otherwise, they are directed to the right side.

The Feature Importance index can be used to specify the importance of each feature in a DT. To achieve this, it is necessary to determine the importance of each node first, and subsequently, the importance of each feature is determined. The importance of node k is calculated using equation 12.

$$\text{Importance\_Node}_k = \frac{\frac{N_k}{N} \times \text{Impurity}_k - \frac{N_{kf}}{N} \times \text{Impurity}_{kf} - \frac{N_{kr}}{N} \times \text{Impurity}_{kr}}{100} \qquad (12)$$

N is the total train data, Nk is the number of instances that exist in node k, kf represents the left sub-node of node k, and Nkf is the number of instances in this sub-node. Similarly, kr represents the right sub-node of node k, and Nkr is the number of instances in this sub-node. The importance of each feature calculated as equation 13.

$$\text{Importance\_feature}_m = \frac{\sum_{m=0}^{M} \text{Importance\_Node}_m}{\sum_{k=1}^{K} \text{Importance\_Node}_k} \qquad (13)$$

Where, Importance_Nodem is node's importance splitting on feature m, M is the number of nodes that split on feature m, and K is the total number of nodes.

Figure 6 represents features importance of DTNF. Based on this graph, C2H2%, C2H2 (ppm), Total (ppm), and C2H6% emerge as the most useful features in DTNF. Other features have less impact on DTNF construction. The sum of the importance of features in a DT is equal to 1.

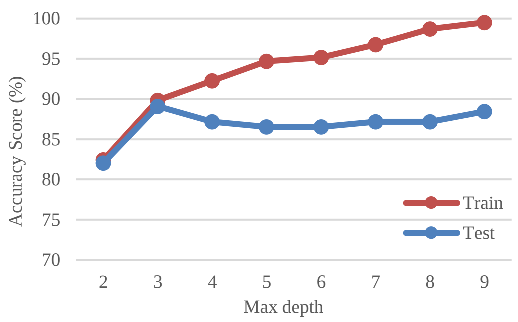

Fig. 3. The performance of DT_{NFG} (DT_{NF} with Gini criterion) on both test and training data.

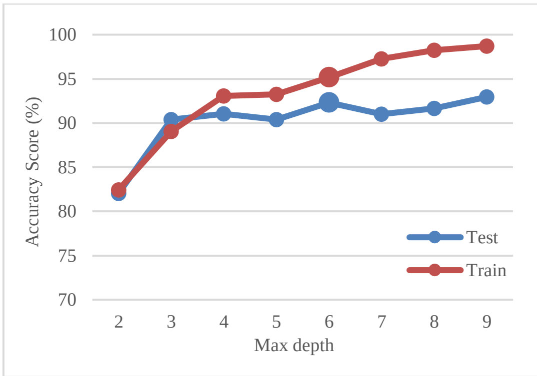

Fig. 4. The performance of DTNFE (DTNF with Entropy criterion) on both test and training data.

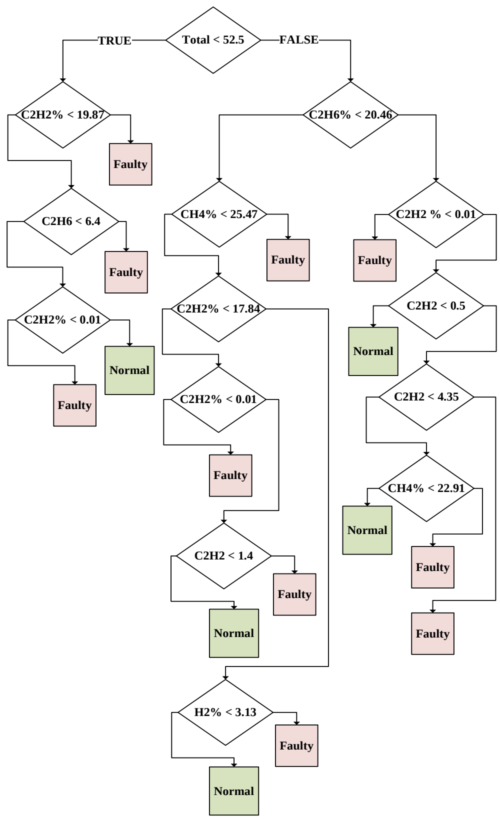

Fig. 5. Final DTNF: Identifying transformer health.

After detecting the fault in the sample, it is necessary to determine the type of fault. This is done in this step by using a specific DT designed to detect the type of fault (DTF).

Figure 7 illustrates the impact of varying the maximum depth on the Accuracy score for a DTF employing the Gini impurity criterion. When the depth of the DT is 2 or 3, it can ultimately distinguish between 2 or 4 fault classes; therefore, the minimum selected depth for the DT in this situation should be 4.

Figure 8 demonstrates how altering the maximum depth influences the Accuracy score in a DTF that utilizes the Entropy impurity criterion.

Based on the information provided in Figures 7 and 8, it is evident that the DT, trained using the Gini impurity criterion, shows superior performance in identifying transformer type faults. Furthermore, as emphasized earlier, a machine learning model is considered effective when its performance remains consistent between training and testing data; therefore, opting for a depth of 5 and the Gini criterion appears to be a suitable choice for DTF.

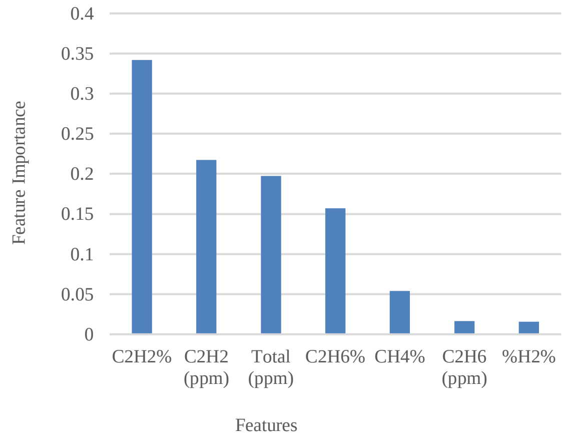

Fig. 6. Final DTNF features importance.

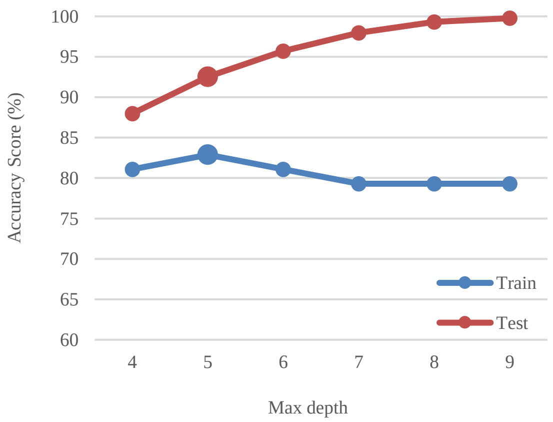

Fig. 7. The performance of DTFG (DTF with Gini criterion) on both test and training data.

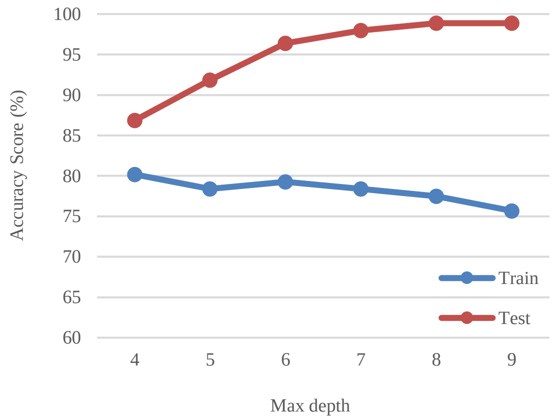

Fig. 8. The performance of DTFE (DTF with Entropy criterion) on both test and training data.

The ultimate DT associated with the Faulty status is presented in Figure 9, comprising a total of 33 nodes. Different fault classes are represented by colored rectangles within the tree, and decision nodes, similar to DTNF in Figure 5, are depicted by rhombuses.

To assess the importance of features in DTF, you can utilize the Feature Importance scale, as per equation 13. Figure 10 illustrates the importance of each feature used in this tree. According to this chart, C2H4%, R3, and H2% stand out as the most valuable features in the DTF model.

In order to create DTs for fault detection, 729 samples have been used. These normal samples were obtained from Alvand Tavan Energy (ATE) Company, and samples containing a type of fault were obtained from Egyptian Electricity Holding Company (EEHC) [14]. These samples contain concentrations of five gases: hydrogen, ethane, methane, ethylene, and acetylene according to Table 2.

Following the introduction of the ultimate DTs for identifying early-stage faults in transformers, it becomes imperative to evaluate the performance of the proposed method. Table 3 shows a comparison between the performance of DTNF and common methods of distinguishing between Normal and Faulty states. According to Table 3, DTNF outperforms the IEEE C57.109 standard, Dornenburg method, and Rogers method by approximately 40%, 50%, and 70%, respectively, in detecting normal samples. Additionally, it exhibits better performance in detecting faulty samples with improvements of 17%, 40%, and 8%, respectively, as indicated by the Recall statistical index. In two-class models, the Accuracy index has the same value for both classes. And DTNF had the best performance in this index.

In Table 4, a performance comparison between DTF and prevalent fault detection methods is presented based on the recall statistical index. The results indicate that DTF showcases the highest performance in all fault classes except T2. Specifically, for the T2 fault class, the IEC 60599 ratio method achieves approximately 10% greater accuracy than DTF, reaching 87.9%. However, when considering all test data, the proposed DTF method surpasses Duval triangle 1, Duval pentagon 1, and IEC 60599 ratio by 13.6%, 14.3%, and 35.2%, respectively.

The utilization of two distinct DTs, namely DTNF and DTF, for sample status detection stems from the substantial distinction between 'Normal' and 'Faulty' samples. Significantly, the 'Total' feature emerges as one of the pivotal factors for discerning the Normal/Faulty state of the samples. Another crucial consideration is ensuring the correctness of the dataset's information; if there are doubts about the accuracy of the information in the dataset, it will impact the confidence level of the model created from it. Therefore, refining the dataset samples using methods outlined in the IEEE C57.104 standard before utilization not only enhances the model's confidence level but also increases the accuracy of the built model due to the more uniform samples. The notations used in Table 2 are T1: Low temperature overheating (T < 300ºC),T2: Medium temperature overheating (300º < T < 700ºC) ,T3: High temperature overheating (T > 700ºC), D1: discharge of low energy, D2: discharge of high energy, PD: Partial discharge.

Table.2.
Count of samples for each fault type.

Normal	PD	D1	D2	T1	T2	T3
177	68	80	139	104	58	103

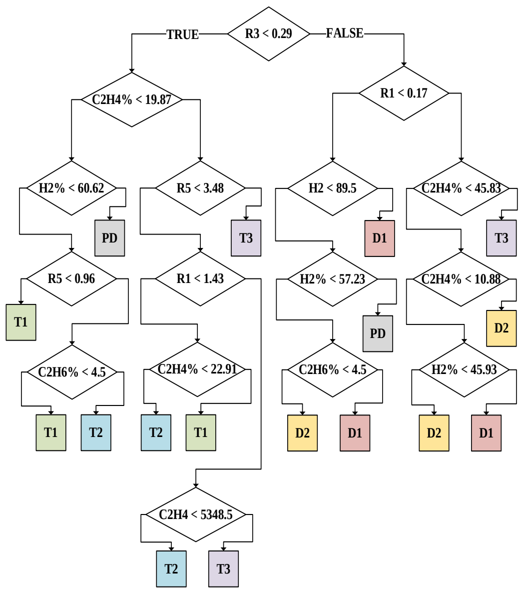

Fig. 9. Final DTF: Identifying the type of fault.

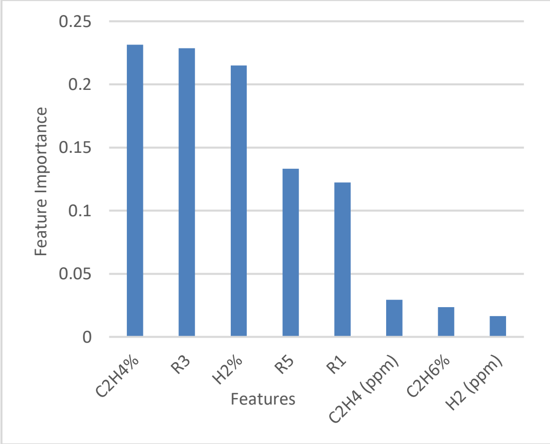

Fig. 10. Final DTF features importance.

Table.3.
Comparative analysis of final DT_{NFE} and common methods for distinguishing between normal and faulty samples on testing data.

Method	***Accuracy (%)***	***Recall (%)***	
	Normal & Faulty	***Normal***	***Faulty***
IEEE C57.109 [3]	69.7	43.6	78.8
Dornenburg [4]	49.0	33.3	54.6
Rogers [5]	68.4	12.8	87.6
DT_{NFE}	92.3	83.0	95.6

Table.4.
Performance comparison of final DT_{FG} and common fault detection methods on testing data.

Method	***Recall (%)***						
	PD	***D1***	***D2***	***T1***	***T2***	***T3***	***All***
Duval Triangle 1 [6]	38.2	78.8	64.8	51.0	48.3	94.2	64.7
Duval Pentagon 1 [7]	39.7	80.0	63.3	49.0	44.8	94.2	64.0
IEC 60599 ratio [15]	22.1	11.3	17.3	60.6	87.9	73.8	43.1
DT_{FG}	62.5	84	76.5	70.2	78.5	94.7	78.3

4. Conclusion

This paper proposes a new approach based on machine learning algorithms, introducing two specialized DTs to detect the Normal/Faulty state and fault type of each sample. The key characteristics of this method are:

The initial step of this paper involves diagnosing the health of transformers, a crucial process given the vital distinction between healthy and defective transformers.

All diagnoses in this method are conducted by individual DTs, characterized by high interpretability. This ensures that the diagnosis of errors or the health of the oil samples is done in a simple and understandable manner.

In test samples, this method demonstrated an accuracy of 92.3% and 82.9%, respectively, in detecting the Normal/Faulty state and identifying the type of fault. In training samples, it achieved an accuracy of 95.2% and 95.5%, respectively, in detecting the Normal/Faulty state and identifying the fault type.

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