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ORIGINAL RESEARCH

Enhancing power transformer health assessment through dimensional reduction and ensemble approaches in Dissolved Gas Analysis

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Abstract

Transformer health analysis using Dissolved Gas Analysis is crucial for diagnosing power transformer faults. This paper proposes an innovative approach to diagnose power transformer faults by integrating machine learning algorithms with Ensemble techniques. The method involves fusing reduced dimensional input features through Principal Component Analysis with Ensemble techniques such as Bagging, Decorate, and Boosting. Various machine learning algorithms, including Decision Tree (DT), K-Nearest Neighbours, Radial Basis Function Network, and Support Vector Machine, are employed in conjunction with Ensemble techniques. The long short-term memory algorithm was used to create synthetic data to solve the issue of data imbalance. A dataset of 683 samples is used in the study for training, testing, validation, and comparison with current techniques. The results highlight the effectiveness of Ensemble techniques, particularly Boosting, which demonstrates superior performance across all classification algorithms. The Boosting with DT algorithm achieves an impressive accuracy of 98.32%, surpassing alternative methods. In validation, the proposed Boosting Ensemble technique outperforms various approaches, showcasing its diagnostic accuracy and superiority over alternative methods. The research emphasises the model's effectiveness in smoothing input vectors, enhancing harmony with ensemble techniques, and overcoming limitations in prior methods.

KEYWORDS

ageing, insulating oils, power transformer insulation

1 | INTRODUCTION

Ensuring the optimal health of power system equipment is crucial for maintaining system reliability. Transformers play a pivotal role in both the distribution and transmission sectors of electrical systems [1]. The power system operates at a high voltage level, underscoring the critical role of transformers in voltage conversion. Prolonged use, however, can inevitably result in internal faults within the transformers [2].

Due to the presence of incipient faults, the insulation within transformers gradually deteriorates, ultimately culminating in failure over time. Consequently, it becomes imperative to monitor the transformers' condition, aiming to enhance machine longevity and mitigate the occurrence of incipient faults [3].

Dissolved Gas Analysis (DGA) stands out as the most crucial method in evaluating the condition of recurrent transformers [4]. Dissolved Gas Analysis serves as a widely adopted online monitoring method globally, primarily employed for the detection of primary faults in oil-filled power transformers. Its popularity stems from the non-destructive monitoring approach and its sensitivity in fault detection [5]. Transformer oil degradation primarily produces the following gases: hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), and carbon monoxide (CO). Interpreting the results involves considering significant parameters, including the combination of rates and concentrations of combustible gases [6]. The rate of gas production serves as a criterion for determining whether the equipment is operating under normal conditions or exhibiting incipient faults [7].

Various methods have emerged to interpret DGA over time. The initial approaches, including Dornenburg's method [8], the International Electrotechnical Commission method [9], and Roger's method [9], all of which are considered methods of ratios. They are improved by a graphical method called the Duval Triangle [10]. The evolution of these techniques has seen a transition from triangles to pentagons, exemplified by the Duval and Mansour pentagons [11, 12]. In more recent times, modern ratio methods have surfaced, such as the clustering method [13] and three ratios techniques [14], alongside graphical innovations such as the Gouda triangle [15]. Despite this progression, both traditional and contemporary methods face challenges in providing accurate interpretations for diagnosing faults in power transformers. Ratios methods encounter difficulties when faults fall outside specified limits, while graphical methods rely on fixed parameters that may not encompass all potential fault scenarios. Furthermore, these methods are susceptible to issues related to the source data.

To address these challenges, artificial intelligence algorithms, encompassing machine learning [16], deep learning [17], Ensemble learning [18], and hybrid techniques [19], have been proposed. These AI-driven solutions aim to transcend the constraints of traditional methods, providing more robust and accurate fault diagnosis for power transformers.

In recent studies, a convergence of traditional DGA methods and artificial intelligence algorithms has been explored to enhance diagnostic capabilities. Senoussaoui and colleagues [20] employed rudimentary vectors, including percentages and logistic ratios, derived from traditional DGA methods. However, they did not utilise these traditional methods as vectors aiding in gas separation. Kherif and team [21], on the other hand, advocated for using traditional DGA methods as vectors, albeit without integrating them. Their evaluation focused solely on accuracy a criterion deemed insufficient for a comprehensive assessment. Hechifa and collaborators [22] took a step further by amalgamating vectors from traditional DGA methods. Nonetheless, their study primarily delved into experimenting with the most suitable vector for algorithms, overlooking the extraction and selection of crucial features within vectors that could enhance efficiency in diagnosing power transformer faults. This underscores the need for a more holistic approach, combining the strengths of traditional DGA methods and artificial intelligence, while optimising feature extraction and selection for improved diagnostic accuracy.

Addressing the limitations of prior methodologies, this paper introduces a novel approach that integrates traditional DGA methods as vectors with ensemble techniques. The proposed model leverages various graphical DGA methods—such as the Duval Triangle, Duval Pentagon, Mansour Pentagon, and Gouda Triangle—by combining them into a single vector to enrich the feature set for power transformer fault diagnosis. To improve computational efficiency and focus on the most informative aspects of the data, Principal Component Analysis (PCA) is applied for dimensionality reduction. However, even with this reduction, the essential diagnostic information is preserved, ensuring that the accuracy of fault diagnosis remains intact. Principal Component Analysis effectively extracts the critical features from the combined DGA methods, allowing the model to retain only the most significant information for classification.

The model further incorporates machine learning algorithms such as Decision Tree (DT), K-Nearest Neighbours, Radial Basis Function Network, and Support Vector Machine (SVM), which are optimised using ensemble techniques such as Bagging, Decorate, and Boosting. These ensemble methods enhance the accuracy and reliability of the diagnosis by reducing variance and improving the stability of the predictions, especially when working with complex or unbalanced datasets.

A major advancement in the proposed model is its ability to address the common challenge of unbalanced datasets, which can significantly affect the performance of fault diagnosis models. By employing Long Short-Term Memory (LSTM) networks to generate synthetic data, the model ensures a balanced dataset, thus improving both the accuracy and consistency of the diagnostic results. This synthetic data generation process mitigates the limitations faced by previous methodologies, where data imbalances could lead to biased or incomplete diagnoses.

Ultimately, the combination of traditional DGA methods, advanced ensemble techniques, and synthetic data generation forms a comprehensive and robust framework for power transformer fault diagnosis. This approach not only resolves the shortcomings of earlier methods, such as ratio-based, graphical, and hybrid techniques, but also offers superior performance, as evidenced by the results from experimental testing. The proposed framework demonstrates significant improvements over existing methodologies, making it a powerful tool for accurate and reliable fault diagnosis in power transformers.

The flow of this article will be as follows. Section 2 provides an explanation of the principles underlying DGA graphical methods. The artificial intelligence (AI) techniques used are described in Section 3. Section 4 will explain the proposed methodology in detail, and Section 5 will discuss, analyse, and compare the results with the existing method. Section 6 will conclude this article with potential future work.

2 | DISSOLVED GAS ANALYSIS GRAPHICAL TECHNIQUES

Dissolved Gas Analysis Graphical Techniques, such as the Duval Triangle Method (DTM), Duval Pentagon Method (DPM), Mansour Pentagon Method (MPM), and Gouda Triangle Method (GTM), have been extensively utilised as vectors for analysing power transformer faults through DGA. These methods have gained recognition for their efficacy in interpreting DGA data, each offering unique insights into the condition of transformers. However, despite their individual effectiveness, there has been a notable absence of efforts to integrate these methods into a single vector, thereby limiting the comprehensive understanding of transformer health. This absence of integration has hindered the exploitation of their complementary properties, potentially missing out on the synergistic benefits that could arise from their combined use. To address this gap, it is essential to delve into the specifics of each graphical method:

2.1 | Duval Triangle Method

Duval Triangle Method, introduced by Canadian scientist Michel Duval, is an alternative graphic approach for analysing dissolved gases using three ratios (R1, R2, and R3) [10]. The method involves dividing a triangle into seven zones, each representing specific faults, and diagnosing faults based on the region to which a point belongs.

2.2 | Duval Pentagon Method

Duval Pentagon Method, developed by Duval and Lamar, is a graphical method for interpreting DGA. It consists of five axes representing the concentrations of five combustible gases (H_2, C_2H_6, CH_4, C_2H_2, and C_2H_4) ranging from 0% to 100% [11], his pentagon delineates six thermal and electrical failure zones, along with a specific area for stray gas(s).

2.3 | Mansour Pentagon Method

Mansour Pentagon Method, entails constructing a pentagon where each vertex represents the percentage concentration of an individual gas relative to the total combustible gases [12]. Similar to the Duval Pentagon, the Mansour Pentagon identifies six thermal and electrical fault zones, differing only in coding.

2.4 | Gouda Triangle Method

Gouda Triangle Method, proposed by Gouda and a group of scientists, is an advanced graphical approach developed from the Duval method. It involves three values (R_1, R_2, R_3) converted into percentages (P_1, P_2, P_3) [15], forming the vertices of a parallelogram triangle similar to the Duval method. The method also identifies fault zones based on these values.

3 | AI TECHNIQUES

This section discusses the various techniques used in the proposed model. While several artificial intelligence algorithms are employed, such as LSTM, DT, SVM, KNN, and Radial Basis Function Networks (RBF), PCA, a statistical method for dimensionality reduction, is also utilised to pre-process the data and improve the performance of these AI algorithms. Additionally, ensemble techniques are incorporated to enhance model robustness.

3.1 | Principal Component Analysis

Principal Component Analysis, initially introduced by Karl Pearson and further developed by Hotelling, is an unsupervised and non-parametric statistical technique widely used in data science and machine learning workflows for dimensionality reduction. Its main objective is to reduce the dimensionality of high-dimensional data by extracting the principal components while preserving as much of the original data's variance as possible. Although not an artificial intelligence algorithm in itself, PCA is often utilised in AI and machine learning tasks to preprocess data and improve the efficiency of subsequent algorithms [23].

3.2 | Long short-term memory

Long short-term memory sophisticated design allows it to effectively understand intricate patterns in sequential data. As a form of recurrent neural network, it considers both previous outputs and current inputs when predicting the next time step, making it adept at capturing complex dependencies. Its application as a time series network is valuable for replicating statistical properties of real-world data in synthetic datasets, especially when privacy preservation is a priority [24]. To avoid generating synthetic data biased by the order of samples, shuffling the dataset before training the LSTM model is a fundamental precaution.

3.3 | Decision Tree

Decision Tree are a distinctive classification algorithm known for their relatively simple structure. Compared to other classification algorithms, DTs excel in efficiently analysing large amounts of data within a short timeframe, making them suitable for mass data processing. A DT classifier is built using internal nodes and leaf nodes, representing decision thresholds and predictions, respectively [25].

3.4 | Support Vector Machine analysis

Support Vector Machine, introduced by Vapnik in the 1990s, is a classifier based on a linear discriminant function and has gained popularity over the past few decades. The success of SVM relies heavily on choosing a suitable kernel function, which generates dot products in a higher-dimensional feature space. This space theoretically extends to infinite dimensions, enabling effective linear discrimination [26].

3.5 | K-Nearest Neighbour

K-Nearest Neighbour algorithm is recognised as one of the simplest intelligent algorithms, notable for its lack of a learning stage. It functions by calculating distances between sample points and their nearest neighbours within the assigned point set. The inductive step involves assigning the class label of the k most similar neighbours to the class label being tested [27].

3.6 | Radial Basis Function Networks

Radial Basis Function Networks (RBFN) serves as an intelligent interpolation technique designed for modelling both linear and non-linear multidimensional data, commonly applied to forecasting problems. The kernel of RBFN involves two parameters: centre and radius. Determining these parameters can be achieved through either unsupervised learning or supervised learning [28].

3.7 | Ensemble techniques

3.7.1 | Bagging

Bootstrap aggregating, commonly referred to as bagging, is an ensemble strategy initially introduced by Breiman. The initial step in the bagging technique involves creating multiple forms, followed by generating models based on the actual method using random subsamples of the dataset [29].

3.7.2 | Decorate

The Diverse Ensemble Creation by Oppositional Relabelling of Artificial Training Examples method, known as Decorate, was introduced by Melville and Mooney. Differing from other ensemble methods, this meta-learning algorithm is distinctive in that it explicitly evaluates and utilises variation in each iteration to generate ensemble classifiers. [30].

3.7.3 | Boosting

The multi-boost learner, also known as boosting, was introduced by Freund and Schapire. Boosting is an ensemble learning technique that combines weak learners to create a strong classifier, enhancing overall accuracy. This sequential ensemble learning method involves training weak learners on a dataset, where the output of one learner becomes the input for the next, iteratively improving the accuracy of the final model [31].

4 | PROPOSED METHODOLOGY

Researcher and engineer are exploring innovative methods with a focus on precision in diagnosis to ensure power equipment safety and extend electrical system lifespan, particularly power transformers. In this endeavour, the proposed methodology aims to introduce novel solutions for diagnosing power transformers. The initial phase involves meticulous data collection, followed by the conversion of this data into input vectors tailored for graphical methods. Subsequently, a normalisation process is applied, accompanied by dimensionality reduction on the input vectors. In the final stage of data processing, a transformation from unbalanced to balanced data is achieved through the integration of synthetic data. Both the original and synthetic datasets are then employed to assess classification algorithms, which are further augmented by the incorporation of ensemble techniques to enhance overall accuracy. The sequential steps of this methodology are visually depicted in Figure 1, with comprehensive explanations provided in this section.

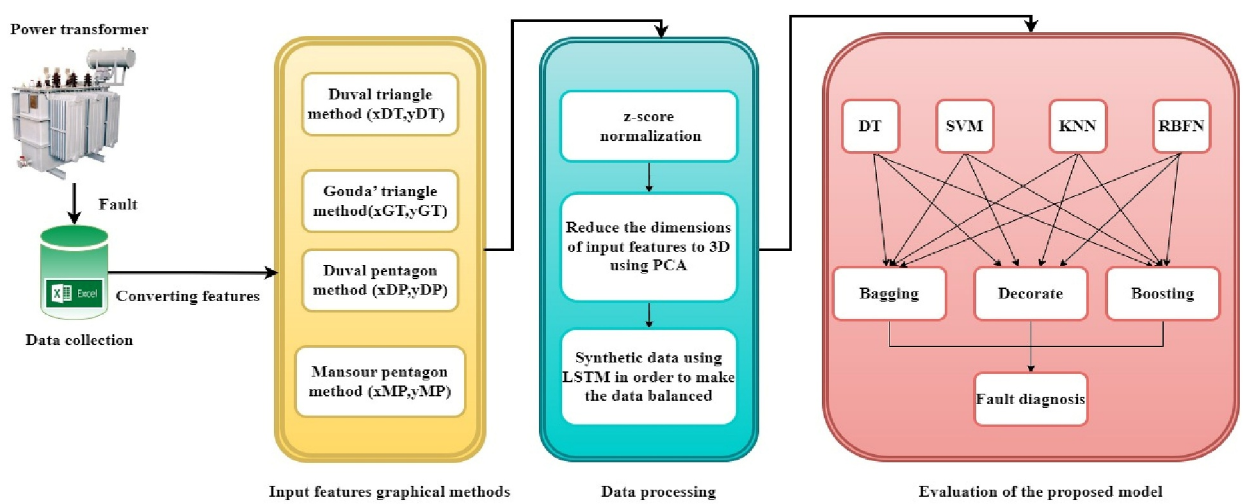


FIGURE 1 Proposed methodology.

4.1 | Dissolved Gas Analysis data collection

Data collection is an important and decisive step in order to evaluate the condition of power transformers, especially with the suffering of the lack of approved data sources, as 407 samples were collected in this study to evaluate the proposed method, from the Egyptian Electricity Company for Transmission and Distribution [32], the IECTC10 databases [33], and the literature [6]. Table 1 shows an example of the data distribution.

4.2 | Input vectors

The transformation of raw data into input vector features is a pivotal step for leveraging graphical methods, such as the Duval Triangle, Duval Pentagon, Mansour Pentagon, and Gouda Triangle. This process is designed to effectively separate overlapping gases, ensuring precision in the analysis. The input features required for the graphical methods are consolidated into a single input vector as illustrated in Table 2.

4.3 | Data processing

4.3.1 | Z-score normalisation

Z-score normalisation, also known as standardisation, is a technique used in statistics to transform data into a standard normal distribution. This process is often applied to features or variables in a data set. The goal is to make the data comparable and suitable for analysis, especially in machine learning and statistical modelling.

The formula for calculating the Z-score for a data point x in a dataset with mean μ and standard deviation σ is given by the following:

$$Z = \frac{x-\mu}{\sigma} \tag{1}$$

Z: the Z-score.
x: the individual data point.
μ: the mean of the dataset.
σ: the standard deviation of the dataset.

Figure 2 illustrates a visual representation employing box plots to depict the dataset both before and after undergoing Z-score normalisation. Visual inspection reveals that the data before normalisation shows outliers, a characteristic mitigated in the normalised dataset where values are confined within the ±3 range. This highlights the efficacy of Z-score normalisation in enhancing data quality, given its ability to centre the data around a mean of 0 with a standard deviation of 1. Notably, this normalisation step holds significance for subsequent dimensionality reduction using PCA in the next step.

TABLE 1 Proposed Dissolved Gas Analysis (DGA) data collection (ppm).

Code	Cases	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2
PD	32	870	77	73	54	14
D1	59	1309	124	113	6	0.001
D2	99	425	17,424	7299	37,043	158
T1	86	244	754	172	1281	27
T2	48	137	369	144	1242	16
T3	83	90	28	8	31	32

Abbreviation: PD, partial discharge.

4.3.2 | Dimensional reduction of features using Principal Component Analysis

The dimensionality reduction step using PCA is crucial for distilling essential information from eight graphical method features, represented as the vector V = [F1, F2, F3, F4, F5, F6, F7, F8]. This process significantly impacts classification algorithms by simplifying feature spaces, improving computational efficiency, and enhancing accuracy. By reducing the number of features while retaining the most informative ones, PCA helps to alleviate the curse of dimensionality, mitigating issues such as overfitting and improving the generalisation capability of machine learning models. Additionally, PCA aids in creating synthetic data, addressing limitations in dataset size. After the 3D conversion, a new vector V' = [n1, n2, n3] is obtained, highlighting the transformation achieved by PCA. The reduced dimensionality not only facilitates visualisation but also contributes to model interpretability. Figure 3 represents the feature conversion proposed for graphical methods applied to 3D features, providing a visual insight into the transformative effects of PCA on the dataset.

TABLE 2 Aggregation of features of graphical methods into the proposed input vector.

Graphical methods	Features equation
Duval triangle method DTM	$F1 = x = 100 - \%C_2H_2 - \%CH_4\, cos\left(\frac{\pi}{6}\right) cot\left(\frac{\pi}{3}\right)$
	$F2 = y = \%CH_4\, cos\left(\frac{\pi}{6}\right)$
Gouda' triangle method GTM	$F3 = x = 100 - \%R_2 - \%R_3\, cos\left(\frac{\pi}{6}\right) cot\left(\frac{\pi}{3}\right)$
	$F4 = y = \%R_3\, cos\left(\frac{\pi}{6}\right)$
Duval pentagon method DPM	$F5 = X(1) = \frac{1}{6} \frac{\sum_{i=0}^{4}(x_i + x_{i+1})(x_i y_{i+1} - x_{i+1} y_i)}{\frac{1}{2}\sum_{i=0}^{4}(x_i y_{i+1} - x_{i+1} y_i)}$
	$F6 = X(2) = \frac{1}{6} \frac{\sum_{i=0}^{4}(y_i + y_{i+1})(x_i y_{i+1} - x_{i+1} y_i)}{\frac{1}{2}\sum_{i=0}^{4}(x_i y_{i+1} - x_{i+1} y_i)}$
Mansour pentagon method MPM	$F7 = x_m = \frac{\sum_{i=1}^{n} m_i x_i}{100}$
	$F8 = y_m = \frac{\sum_{i=1}^{n} m_i y_i}{100}$
Proposed vector	V = [F1, F2, F3, F4, F5, F6, F7, F8]

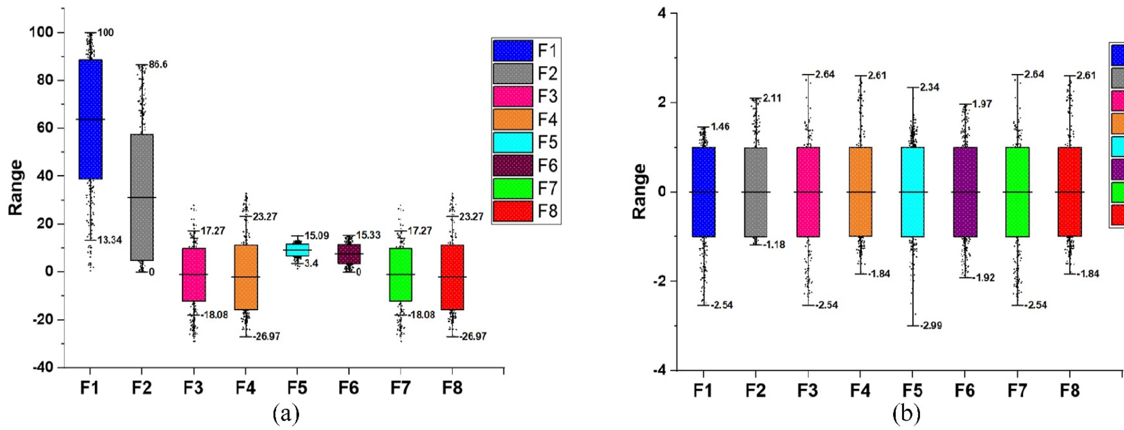


FIGURE 2 Examine outliers using Z-score normalisation; (a) Before Z-score normalisation; (b) After Z-score normalisation.

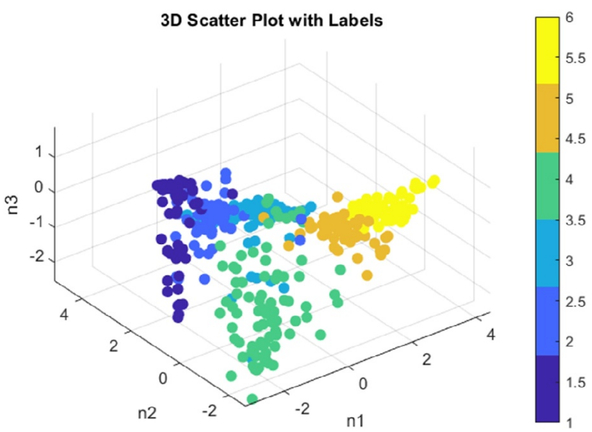


FIGURE 3 Principal Component Analysis (PCA) transformation of 3D features.

4.3.3 | Creating synthetic data using long short-term memory

To enhance the diagnostic accuracy of classification algorithms, a strategy has been proposed to transform the imbalanced dataset into a balanced one. This involves generating synthetic data to ensure an equitable representation of faults, aligning with the principle of equal opportunity in fault evaluation. Examining Table 1 reveals that fault D_1 stands out with the highest count of 99 samples, making it the benchmark. Synthetic data will be introduced to each of the faults, namely partial discharge (PD), D_2, T_1, T_2, and T_3, until their counts match that of D_1.

The synthetic data generation process employs LSTM networks, chosen for their capability to create multi-modal tabular data. LSTMs are particularly suited to handling a mixture of categorical, numeric, time-series, and textual fields, as they are designed to capture long-range dependencies and maintain context over sequences of data.

Relevant references have been provided [37, 38] to offer further explanation of the underlying principles of LSTM networks in this context, including how they effectively capture temporal dependencies and preserve statistical interdependencies. Figure 4 from Gretel's report illustrates a comparative analysis of correlation matrices, showcasing the relationships between variables in both the original training set and the synthetic dataset generated by the LSTM. The figure further quantifies the discrepancies between the two sets, providing a measure of the LSTM's ability to preserve the integrity of the data relationships during synthesis.

4.4 | Evaluation of the proposed model

4.4.1 | Hyperparameters for classification algorithms

After generating synthetic data, employing hyperparameters becomes crucial to shape the behaviour of machine learning models. The meticulous selection and fine-tuning of these hyperparameters play a pivotal role in bolstering the predictive capabilities of the proposed model. A model endowed with thoughtfully chosen hyperparameters is predisposed to consistently exhibit optimal performance and effectively mitigate the risk of overfitting. Notably, the hyperparameters outlined in Table 3 were utilised during the training of the proposed model.

4.4.2 | Evaluation metrics

The meticulous selection of appropriate evaluation metrics stands as a critical factor in gauging the efficacy and reliability of the proposed model. Essential metrics such as Accuracy, Recall, Precision, Specificity, and F1-Score collectively contribute to a thorough assessment, offering insights into the model's performance across various dimensions. These metrics are widely recommended in the literature [34–36].

Accuracy: Measures the overall correctness of the model by calculating the ratio of correct predictions (both true positives and true negatives) to the total number of predictions:

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \quad (2)$$

Precision: Evaluates the proportion of true positives among all predicted positives, indicating how many of the predicted positive instances are actually correct:

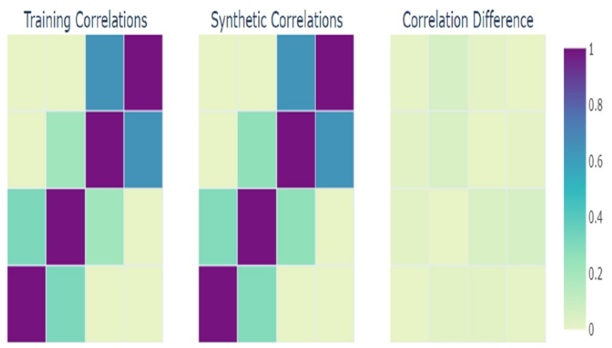


FIGURE 4 Synthetic data generation report.

TABLE 3 Hyperparameters of the AI techniques used.

Algorithms	Parameters	Values
DT	Collapse tree	True
	Confidence factor	0.25
	Num folds	3
	seedn	1
SVM	SVM type	C-SVC
	Cache size	40
	Degree	3
	Kernel type	Radial basis function
KNN	k	2
	Search algorithm	Linear NN search
RBFN	Clustering seed	1
	maxIts	−1
	Num clusters	2
	Ridage	1.0E-8
Ensemble techniques		
Bagging	Bag size percent	100
	Num execution slots	1
	Num iterations	10
Decorate	Artificial size	1
	Desired size	15
	Num iterations	50
Boosting	Num sub cmtys	3
	Weight threshold	100
	Num iterations	10

Abbreviation: AI, artificial intelligence.

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

Recall (Sensitivity): Measures the model's ability to correctly identify positive instances from the dataset, focussing on capturing all true positives:

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

Specificity: Complements Recall by measuring the model's ability to correctly identify negative instances, evaluating how well the model avoids false positives:

$$Specificity = \frac{TN}{TN + FN} \quad (5)$$

F1-Score: Provides a harmonic mean of Precision and Recall, ensuring a balanced evaluation of both metrics, especially when a trade-off exists between them:

$$F1 - Score = \frac{2(Precision \times Recall)}{Precision + Recall} \quad (6)$$

where, TP is true positives, TN is true negatives, FP is false positives, FN is false negatives.

5 | RESULTS AND DISCUSSION

5.1 | Implementation and analysis of results

The proposed model was implemented using the KNIME analytics platform, an open-source tool tailored for developing data analyses and predictive models. KNIME leverages various programming languages and frameworks, including Python, Java, and Weka, to construct its analytical workflows. To assess the model's performance, a dataset comprising 407 real, unbalanced samples and 187 synthetic samples was employed, resulting in a hybrid balanced dataset of 594 samples. The dataset was split in a 70:30 ratio, with 70% used for training and 30% for testing. The effectiveness of the model was evaluated using the hybrid balanced dataset and compared against the real unbalanced data to provide deeper insights into the model's robustness. Figure 5 illustrates the sequential steps involved in implementing the ensemble classification algorithms within the proposed model.

Tables 4 and 5 present key metrics evaluating the performance of the proposed ensemble classification algorithms. The metrics Accuracy, Recall, Precision, Specificity, and F1-Score provide a comprehensive assessment of the model's effectiveness across different algorithms and ensemble techniques, including base, Bagging, Decorate, and Boosting. These results enable a comparison between real and hybrid datasets.

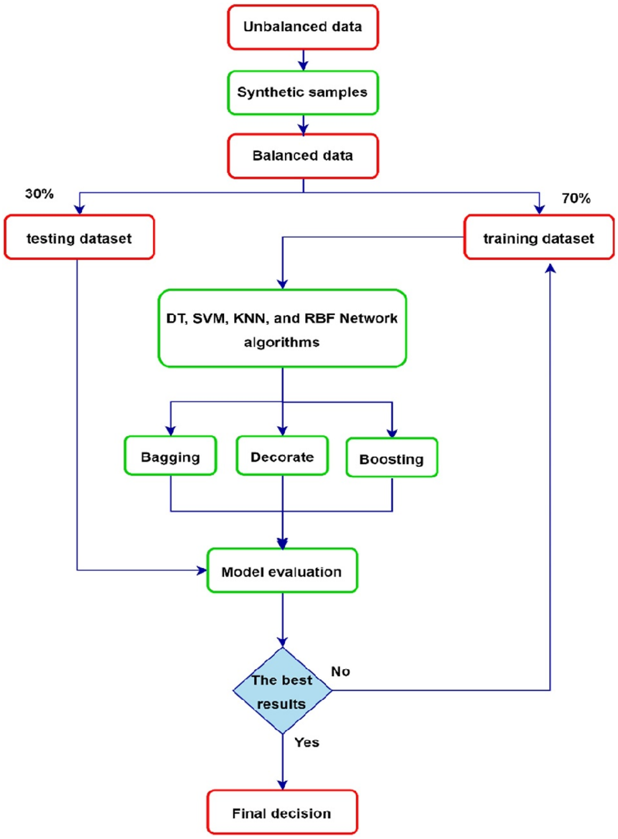


FIGURE 5 Flowchart for implementing the proposed method.

Boosting consistently emerges as the best-performing ensemble technique across all algorithms and datasets, particularly excelling in accuracy, recall, and F1-score. It shows clear advantages with more complex models like those using hybrid datasets. Bagging also delivers strong performance, frequently ranking as the second-best technique, especially in recall and specificity.

In contrast, Decorate tends to underperform relative to Bagging and Boosting, particularly with real datasets, though it demonstrates moderate improvements with hybrid datasets. Overall, this analysis highlights Boosting as the most robust technique across different algorithms, with Bagging being a strong competitor. While Decorate is less effective, particularly in real datasets, it performs better with hybrid datasets. This comparison provides clear insights into how different ensemble methods impact the performance of classification algorithms based on the dataset type.

A thorough analysis of Table 6 and Figure 6 clearly demonstrates that the use of balanced hybrid data significantly outperforms real unbalanced data, with Boosting exhibiting the highest performance when paired with the DT algorithm in both cases. The algorithm achieved outstanding results with an accuracy of 98.32%, recall of 98.31%, precision of 98.38%, specificity of 99.67%, and an F1 score of 98.33% when applied to hybrid data. Notably, these values not only surpassed but substantially exceeded those of all other ensemble classification techniques, providing strong empirical evidence both visual and tabular that highlights the superior performance of Boosting

TABLE 4 Metrics to evaluate the performance of the proposed ensemble classification algorithms for real datasets.

		Model evaluation (%)				
Algorithm	**Ensemble techniques**	**Accuracy**	**Recall**	**Precision**	**Specificity**	**F1-score**
Decision tree (DT)	Base	86.99	86.64	85.26	97.40	85.71
	Bagging	88.62	85.84	88.76	97.67	86.33
	Decorate	86.99	86.09	86.73	97.34	86.08
	Boosting	**89.43**	**88.22**	**89.66**	**97.81**	**88.44**
K-nearest neighbours (KNN)	Base	85.37	84.19	84.61	97.01	83.71
	Bagging	87.80	86.97	87.14	97.52	86.65
	Decorate	86.18	84.72	85.32	97.19	83.98
	Boosting	**88.62**	**86.93**	**88.87**	**97.64**	**87.14**
Radial basis function network (RBFN)	Base	83.80	81.82	82.33	96.72	81.80
	Bagging	84.55	82.77	85.48	96.79	82.96
	Decorate	80.49	77.61	80.46	95.99	76.99
	Boosting	**87.80**	**84.91**	**88.10**	**97.50**	**85.52**
Support vector machine (SVM)	Base	76.42	72.32	84.87	94.98	68.95
	Bagging	78.05	74.36	85.69	95.33	72.04
	Decorate	73.98	68.80	83.37	94.48	63.27
	Boosting	**79.67**	**76.03**	**86.04**	**95.70**	**74.71**

Note: The bold represents the best results.

TABLE 5 Metrics to evaluate the performance of the proposed ensemble classification algorithms for hybrid datasets.

		Model evaluation (%)				
Algorithm	**Ensemble techniques**	**Accuracy**	**Recall**	**Precision**	**Specificity**	**F1-score**
Decision tree (DT)	Base	95.53	95.52	95.83	99.11	95.55
	Bagging	96.09	96.06	96.18	99.22	96.07
	Decorate	96.65	96.64	96.87	99.33	96.66
	Boosting	**98.32**	**98.31**	**98.38**	**99.67**	**98.33**
K-nearest neighbours (KNN)	Base	95.53	95.50	96.07	99.11	95.59
	Bagging	97.21	97.18	97.50	99.44	97.23
	Decorate	96.09	96.07	96.32	99.22	96.12
	Boosting	97.77	97.94	97.95	99.55	97.78
Radial basis function network (RBFN)	Base	94.41	94.43	94.45	98.89	94.44
	Bagging	95.53	95.54	96.70	99.11	95.59
	Decorate	94.41	94.43	94.46	98.89	94.42
	Boosting	97.21	97.21	97.35	99.44	97.24
Support vector machine (SVM)	Base	96.09	96.09	96.23	99.22	96.10
	Bagging	95.53	95.54	95.61	99.11	95.55
	Decorate	94.41	94.43	94.53	98.89	94.40
	Boosting	97.77	97.78	97.92	99.55	97.78

Note: The bold represents the best results.

TABLE 6 A comprehensive overview of all boosting results.

Boosting	**Acc**	**Rec**	**Pre**	**Spe**	**F1-S**
Unbalanced real data evaluation (%)					
DT	89.43	88.22	89.66	97.81	88.44
KNN	88.62	86.93	88.87	97.64	87.14
RBFN	87.80	84.91	88.10	97.50	85.52
SVM	79.67	76.03	86.04	95.70	74.71
Balanced hybrid data evaluation (%)					
DT	98.32	98.31	98.38	99.67	98.33
KNN	97.77	97.94	97.95	99.55	97.78
RBFN	97.21	97.21	97.35	99.44	97.24
SVM	97.77	97.78	97.92	99.55	97.78

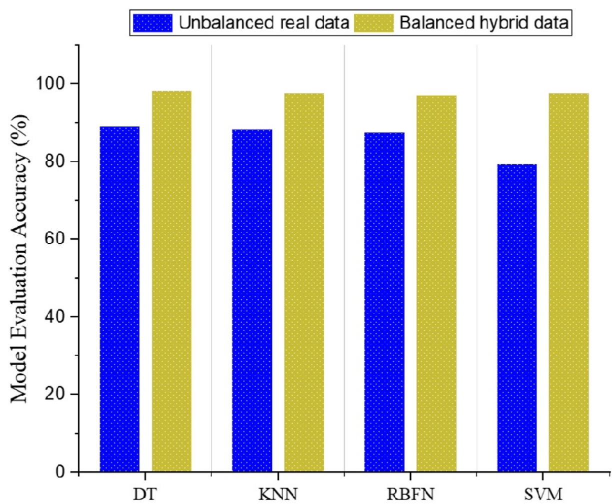


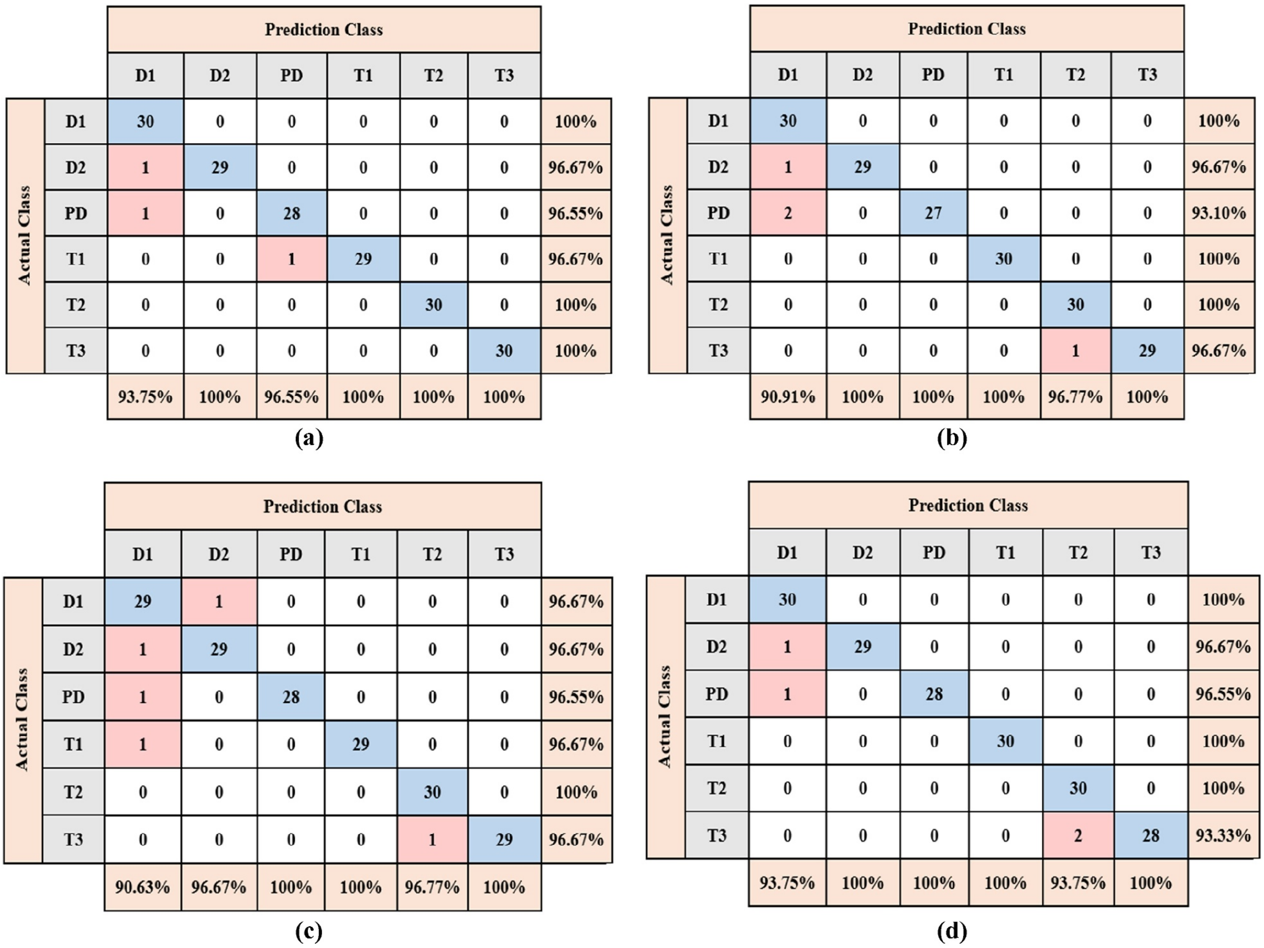
FIGURE 6 Comparison of the best results of boosting between balanced and unparallel data.

when combined with the DT algorithm. This underscores its position as the optimal choice among ensemble classification strategies.

Figure 7 presents the confusion matrices for the best results achieved by Boosting across four different algorithms DT, KNN, RBFN, and SVM labelled as (a), (b), (c), and (d), respectively. Each matrix compares predicted and actual classes for six distinct faults (D_1, D_2, PD, T_1, T_2, and T_3), with the values representing correct and incorrect predictions, and percentages reflecting the classification accuracy for each fault.

When using hybrid data, which balances real and synthetic samples, Boosting significantly improves the classification accuracy of all algorithms. However, the DT algorithm (A) clearly outperforms the others. Decision Tree achieves near-perfect results, with 100% correct classification on four out of six faults, with two misclassifications in "D_1" and one in "T_1." This highlights the superior capability of the DT algorithm to effectively manage hybrid data and consistently maintain high performance across various fault types.

In comparison, KNN (B) also performs well with hybrid data, achieving 100% accuracy on three faults, but it experiences one misclassification in "D_1," two in "PD," and one in "T_3." Similarly, RBFN (C) and SVM (D) benefit from hybrid



(a)

Actual Class \ Prediction Class	D1	D2	PD	T1	T2	T3	
D1	30	0	0	0	0	0	100%
D2	1	29	0	0	0	0	96.67%
PD	1	0	28	0	0	0	96.55%
T1	0	0	1	29	0	0	96.67%
T2	0	0	0	0	30	0	100%
T3	0	0	0	0	0	30	100%
	93.75%	100%	96.55%	100%	100%	100%	

(b)

Actual Class \ Prediction Class	D1	D2	PD	T1	T2	T3	
D1	30	0	0	0	0	0	100%
D2	1	29	0	0	0	0	96.67%
PD	2	0	27	0	0	0	93.10%
T1	0	0	0	30	0	0	100%
T2	0	0	0	0	30	0	100%
T3	0	0	0	0	1	29	96.67%
	90.91%	100%	100%	100%	96.77%	100%	

(c)

Actual Class \ Prediction Class	D1	D2	PD	T1	T2	T3	
D1	29	1	0	0	0	0	96.67%
D2	1	29	0	0	0	0	96.67%
PD	1	0	28	0	0	0	96.55%
T1	1	0	0	29	0	0	96.67%
T2	0	0	0	0	30	0	100%
T3	0	0	0	0	1	29	96.67%
	90.63%	96.67%	100%	100%	96.77%	100%	

(d)

Actual Class \ Prediction Class	D1	D2	PD	T1	T2	T3	
D1	30	0	0	0	0	0	100%
D2	1	29	0	0	0	0	96.67%
PD	1	0	28	0	0	0	96.55%
T1	0	0	0	30	0	0	100%
T2	0	0	0	0	30	0	100%
T3	0	0	0	0	2	28	93.33%
	93.75%	100%	100%	100%	93.75%	100%	

FIGURE 7 Confusion matrix for the best boosting results for DT (a), KNN (b), RBFN (c), and SVM (d).

data but show more frequent misclassifications. Notably, SVM (D) demonstrates the lowest performance among the four algorithms, particularly in the classification of the "T_3" fault.

Overall, the results confirm the effectiveness of Boosting in conjunction with hybrid data, significantly enhancing classification performance across all algorithms due to the balanced synthetic data generated using LSTM. Additionally, the benefits of dimensionality reduction through PCA are evident in the improved interpretability and generalisation of the results. By reducing the feature space while preserving essential information, PCA contributes to a clearer understanding of the performance metrics, offering insights into the underlying factors driving the superior performance of Boosting when combined with the DT algorithm. Consequently, dimensionality reduction enhances the robustness and reliability of the results, further reinforcing the validity of the conclusions drawn from this analysis.

5.2 | Validation and comparison with existing methods

For validation and comparison, a new dataset from the literature, comprising 89 samples, was employed to assess the efficiency of the proposed model and to compare it with current methods. These 89 samples as detailed in ref. [22], serve as a basis for assessing the performance of the proposed model and for comparative analysis with established methodologies.

Table 7 presents a comprehensive comparison between the results achieved by the proposed model and existing methodologies across various categories, namely DGA Ratios methods, DGA graphical methods, intelligent methods, and hybrid methods. The assessment is based on the accuracy pertaining to specific faults (PD, D_1, D_2, T_1, T_2, and T_3) as well as the overall accuracy. Notably, the Proposed Boosting Ensemble techniques exhibited superior performance in contrast to the Current methods. Specifically, for DT, K-Nearest Neighbours, Radial Basis Function Network, and SVM, the Proposed Boosting Ensemble demonstrated overall accuracies of 95.51%, 94.38%, 92.13%, and 93.26%, respectively. This underscores the effectiveness of the proposed model across a spectrum of fault types and its ability to outperform existing methodologies in multiple scenarios.

Figure 8 illustrates a comprehensive comparison between the optimal outcomes obtained through the Proposed Boosting Ensemble techniques and the best results achieved by various categories of existing methods, including Ratios methods, graphical methods, intelligent methods, and hybrid methods. Notably, the Boosting DT algorithm stands out by achieving the highest diagnostic accuracy at 95.51%, surpassing all other existing methods. Specifically, it outperforms the clustering method with 83.15%, the GTM with 78.65%, the

TABLE 7 Validation and comparison with existing methods.

	Existing methods	PD	Accuracy (%)					
			D_1	D_2	T_1	T_2	T_3	Total
DGA ratios methods	Modified IEC 60599 [9]	87.50	61.54	84.21	84.62	57.14	89.66	80.90
	Three ratios technique [14]	75	46.15	89.47	69.23	71.43	93.10	78.65
	Clustering method [13]	100	69.23	84.21	92.31	42.86	89.66	83.15
	Key gases with gas ratios [39]	75	76.92	84.21	84.62	57.14	82.76	79.78
DGA graphical methods	Duval triangle method [10]	75	53.85	78.95	53.85	57.14	89.66	73.03
	Duval pentagon method [11]	62.50	15.38	63.16	76.92	57.14	89.66	66.29
	Mansour pentagon method [12]	87.50	61.54	63.16	53.85	14.29	82.76	66.29
	Gouda triangle method [15]	87.50	69.23	84.21	53.85	57.14	93.10	78.65
Intelligent methods	CSUS ANN method [17]	75	38.46	68.42	92.31	14.29	62.07	61.80
	Trees based learning [22]	100	92.31	89.47	92.31	85.71	93.10	92.13
	Conditional probability method [16]	87.50	53.85	89.47	61.54	57.14	93.10	78.65
Hybrid methods	Combined technique N°2 [19]	87.50	69.23	89.47	61.54	71.43	89.66	80.90
	Combined technique N°3 [19]	87.50	69.23	89.47	61.54	71.43	82.76	78.65
	Novel combined techniques [40]	87.50	53.85	84.21	76.92	00.00	86.21	73.03
Proposed boosting ensemble techniques	Decision tree	**100**	**100**	**89.47**	**100**	**87.50**	**96.43**	**95.51**
	K-nearest neighbours	100	92.31	94.74	100	87.50	92.86	94.38
	Radial basis function network	100	92.31	78.95	92.31	100	96.43	92.13
	Support vector machine	100	92.31	89.47	100	87.50	92.86	93.26

Note: The bold represents the best results.

Abbreviations: ANN, artificial neural network; IEC, International Electrotechnical Commission; PD, partial discharge.

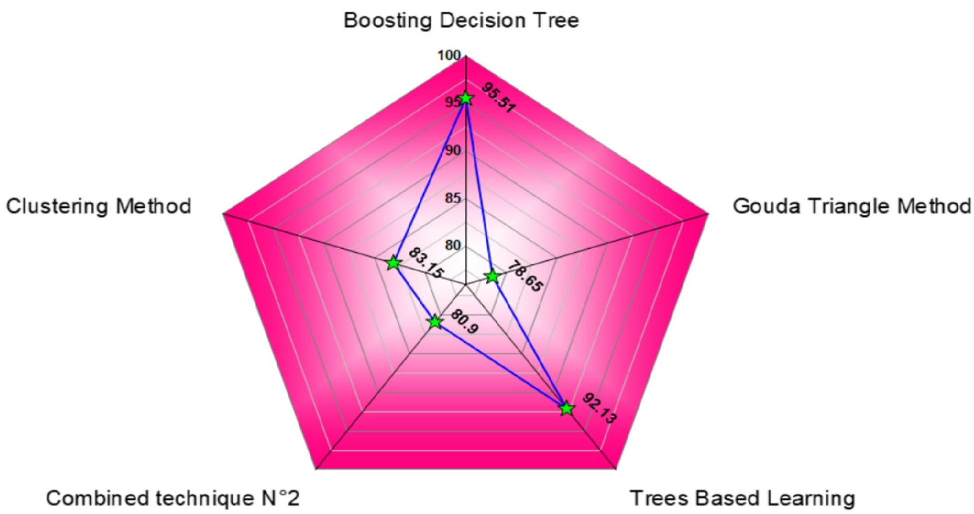


FIGURE 8 Compare the best results for each category of previous methods with the best proposed method.

Trees Based Learning algorithm with 92.13%, and the combined technique N°2 with 80.90%. The superiority of Boosting DT can be attributed to its utilisation of graphical methods as vectors, which are then subjected to dimensionality reduction techniques such as PCA, thereby enhancing the discrimination power of the algorithm. Moreover, the boosting property of the algorithm, which iteratively improves the model's performance by focussing on misclassified instances, synergistically overlays with the DT's ability to capture complex relationships in the data, resulting in superior classification accuracy.

6 | CONCLUSION

This contribution introduced an innovative approach by amalgamating machine learning algorithms with Ensemble techniques for the purpose of diagnosing power transformer faults. The method hinged on the fusion of reduced-dimensional input features via PCA with Ensemble techniques encompassing Bagging, Decorate, and Boosting, in conjunction with machine learning algorithms such as DT, KNN, RBFN, and SVM. Utilising a dataset comprising 683 samples, including 594 from literature and synthetic sources for training and testing, and 89 for validation and comparison with existing methods, the findings underscored the efficacy of Ensemble techniques, with Boosting exhibiting superior performance across all classification algorithms. Specifically, the Boosting with DT algorithm attains an impressive accuracy of 98.32%, surpassing K-Nearest Neighbours 97.77%, Radial Basis Function Network 97.21%, and SVM 97.77%. In validation and comparison with existing methods, our proposed Boosting Ensemble technique outshines various approaches, including Ratio methods, graphical methods, intelligent methods, and hybrid methods. Notably, the Boosting DT algorithm exhibits a diagnostic accuracy of 95.51%, showcasing its superiority over alternative methods such as clustering 83.15%, GTM 78.65%, Trees Based Learning 92.13%, and Combined technique N°2 80.90%. This superior performance underscores the effectiveness of the model in smoothing input vectors, enhancing harmony with ensemble techniques, and mitigating limitations inherent in prior methods. The successful integration of the proposed model not only advanced diagnostic accuracy but also paved the way for future research. Researchers can explore feature extraction and selection, combining them with machine learning algorithms, deep learning, and Ensemble techniques. Leveraging DGA input vectors enhances diagnostic model reliability, offering promising avenues for continued advancements in the field.

AUTHOR CONTRIBUTIONS

Abdelmoumene Hechifa: Conceptualisation; Formal analysis; Methodology; Software; Validation; Writing - original draft; Writing - review & editing. **Saurabh Dutta**: Formal analysis; Methodology; Writing - original draft; Writing - review & editing. **Abdelaziz Lakehal**: Formal analysis; Methodology; Supervision; Writing - original draft. **Hazlee Azil Illias**: Formal analysis; Methodology; Supervision. **Arnaud Nanfak**: Formal analysis; Methodology; Supervision; Writing - review & editing. **Chouaib Labiod**: Formal analysis; Methodology; Supervision.

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CONFLICT OF INTEREST STATEMENT

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PERMISSION STATEMENT TO REPRODUCE THE MATERIALS FROM THE OTHER SOURCES

None.

DATA AVAILABILITY STATEMENT

Data available on request from the authors.

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