https://doi.org/10.5755/j02.eie.39824 ELEKTRONIKA IR ELEKTROTECHNIKA, ISSN 1392-1215, VOL. 31, NO. 3, 2025

A Comprehensive Review of Transformer Fault Diagnosis Studies Based on Dissolved Gas Analysis: Classical Methods, Historical Development of the Devices Used, Artificial Intelligence Based Methods, Accuracy of Classifications of Predictions

Nurullah Acikgoz[1,*], Murat Husnu Sazli[1], Ilhan Kosalay[2]
[1]*Department of Electrical and Electronics Engineering, Faculty of Engineering, Ankara University, Ankara, Turkiye*
[2]*Department of Electrical and Electronics Engineering, Faculty of Engineering, Necmettin Erbakan University, Konya, Turkiye*
[*]*nacikgoz@ankara.edu.tr; sazli@eng.ankara.edu.tr; ilhan.kosalay@erbakan.edu.tr*

***Abstract*—Transformers are critical and expensive components of power systems. Therefore, it is important that these systems operate at optimum performance levels and sustainable economic conditions. In the normal operating environments, mineral oil passes on a slow and natural deterioration, while under conditions of thermal or electrical stress, the deterioration ratio increases. Due to breakdown, the hydrocarbon gases H2, CH4, C2H6, C2H4, C2H2, CO, and CO2) are composed in the transformer mineral oil. There are several conventional methods for identifying and classifying incipient faults in power transformers based on dissolved gas analysis (DGA). However, these methods have the disadvantage of not being able to distinguish situations where multiple electrical or thermal faults occur simultaneously. Due to the serious disadvantage of traditional DGA methods in terms of accuracy and consistency estimation compared to algorithm calculations made with artificial intelligence techniques, researchers have started to work intensively on artificial intelligence techniques in recent years. This comprehensive review aims to combine and present in a single source basic information about classical methods of power transformer fault diagnosis for DGA, historical development of the devices used, artificial intelligence-based methods, accuracy classifications of predictions. This investigation also revealed the contribution of the parameter optimisation process to eliminate the imbalance of the dataset in the accuracy of prediction when applying artificial intelligence techniques in DGA. In this study, the prediction performance of each research method performed with artificial intelligence techniques in fault diagnosis among the compared methods was analysed. This review emphasises the importance of eliminating dataset imbalance by performing parameter optimisation in artificial intelligence technique with an in-depth research-orientated perspective. As a result, this study not only encourages new ideas, but also provides a comprehensive source of literature for future accessibility of the subject.**

Manuscript received 31 March, 2025; accepted 8 June, 2025.

***Index Terms*—Oil-immersed power transformer; Dissolved gas analysis (DGA); Fault diagnosis; Artificial intelligence techniques.**

I. INTRODUCTION

Power transformers are the main components of power systems, and early diagnosis of power transformer faults is the biggest factor in maintaining the stability of the power system. The method known as dissolved gas analysis is a frequently used diagnostic technique to detect possible faults in power transformers based on the IEEE C57.104 standard with the dissolved gas concentration in oil transformers and the ratios obtained from these gases [1].

There are seven basic error types that can be identified using the dissolved gas analysis (DGA) method, as listed below, based on IEC 60599 and IEEE C.57.104. In addition, due to the limited information available in the datasets, in some cases, these failure types are divided into three broader categories. These are partial discharge (PD), energy discharges, and thermal faults. Below are fault condition definitions explaining the abbreviations PD1, PD2, D1, D2, T1, T2, T3, DT, and UD [1]–[3]:

- PD1 Low-energy corona-partial discharge;
- PD2 High-energy corona-partial discharge;
- D1 Electrical discharge of low energy;
- D2 Electrical discharge of high energy;
- T1 Thermal faults of temperature $T < 300$ °C;
- T2 Thermal faults, 300 °C $< T < 700$ °C;
- T3 Thermal faults, $T > 700$ °C;
- DT Thermal & Electrical fault mixture;
- UD Undetermined fault.

DGA is defined as a key element that is commonly applied to assign defects in oil-filled power transformers [3], [4]. If unlike thermal and electrical stresses, this will cause oil insulation so that breaks down the transformer, then escaping and dissolving some gases occurs. The release of the main gases dissolved in DGA indicates faulty parts of the power transformer. These gases, respectively, are oxygen and nitrogen, which indicates a leak in a sealed tank. Other released gases are carbon monoxide and carbon dioxide, which indicates cellulose or paper degradation inside the transformer [5], [6].

In power transformers, in random operating surroundings, mineral oil passes inherently deterioration, whereas under thermal or electrical stress conditions this rate of deterioration increases. The contact of transformer oil with air and the deterioration of the insulation in cellulose also cause the release of the specified gases in transformer oil. In these cases, the priority order of the gases released according to the type of fault is as follows: Hydrogen, methane in corona discharge fault, hydrogen, acetylene, ethane, ethylene in arcing fault, ethylene, methane, acetylene in transformer oil overheating, carbon monoxide in transformer internal winding insulation overheating, respectively. Hydrogen gases are produced [7].

The stages of the emergence of gases as the transformer oil heats up are summarised as follows. It can be seen that 350 ◦C is critical for the C2H4 formation. Also, between 500 ◦C–700 ◦C is an important gap for C2H2 occurings. If the temperature is above 700 ◦C, small amounts of C2H2 form under a thermal fault. At approximately 450 ◦C, more C2H2 is formed. When this temperature reaches 750 ◦C–800 ◦C, the H2 production is higher than other gases. As a function of the fragmentation energy, the gas volumes in the oil continue to increase according to the temperature threshold values. Little quantity of H2 and CH4 begin to occur at a low temperature of 150 ◦C. There is another important temperature point, which is 275 ◦C. This tempererature is the beginning of the formation of ethane (C2H6). The temperature gap of 200 ◦C–300 ◦C means that the amount of CH4 gas released is greater than the amount of H2 gas released. According to the specific temperature defined above, the common point of these gases is the combustible gas generation. In case of any interference of these released gases with oxygen, there will be a fire that could be very dangerous for the transformer which is connected to the electrical distribution system, so the effect of the fire fault can cause several root problems [7]–[9].

As discussed in detail in Section II, it has been observed that the proposed artificial intelligence algorithms exhibit successful fault prediction performance despite the serious shortcomings of classical methods in fault diagnosis in DGA. In terms of the instability of various error types, the traditional ML diagnosis method has some complexity. On the other hand, there may be many uncertain and unstable values in the dataset used for DGA studies. Therefore, the main innovation of this work is the construction of the artificial intelligence model with a robust parameter optimisation strategy, which performs well in fault prediction and is resilient to uncertainty.

The main contribution of the article consists of some important highlights. Detailed information on the electrical, physical, thermal, and chemical properties in the formation of DGA is discussed, which contributes significantly to a comprehensive understanding of the subject. In the study, the prediction performances of all algorithms made with machine learning are explained with tables and graphs. The main purpose of the study is to combine and present basic information on classical methods in power transformer fault diagnosis for DGA, historical development of the devices used, artificial intelligence-based methods, and accuracy of classifications of predictions in a single source.

The article is divided into five sections as follows. In Section II, we mention the classical methods for dissolved gas analysis and the inconsistencies of the prediction results obtained from the classical methods. In Section III, the historical development of the devices used in DGA is given. In Section IV, the contribution of parameter optimisation in machine learning algorithms to the individual and hybrid artificial intelligence methods used in DGA on the prediction accuracy is analysed. In Section V, in studies carried out with artificial intelligence methods, the quantity and source of the dataset, the compared methods, the type of programming, the prediction accuracy rate, and the status of the method used in fault diagnosis are revealed and the prediction classification is carried out chronologically. Finally, in Section VI, the article is concluded by analysing the numerical data obtained.

II. HISTORICAL BACKROUND FOR CLASSICAL METHODS OF DISSOLVED GAS ANALYSIS

When more than 250 sources were inspected in the comprehensive literature review covering the years 2000–2024, it was understood that the traditional methods based on dissolved gas analysis were mainly key gas, Duval triangle, IEC ratio, Rogers ratio, Nomograph, and Doernenburg method. These methods are listed as follows: IEC ratio method, Duval triangle method, Duval Pentagon method, Doernenburg ratio method, key gas method, Roger’s ratio method, nomograph method, low-energy degradation triangle method [10]–[13].

As a DGA fault interpretation technique, some classical methods that are slightly different from the eight main methods have also been developed. Each of the eight main known conventional techniques has its own calculation method for assessing the condition of the transformer. In view of the above, this article provides review to explain eight DGA techniques to interpret the same data obtained from any sample of power transformer oil [14]–[17]. Compared to DGA methods, the IEC 60599 standard is a useful procedure for the IEC ratio method whereas the other traditional methods use the IEEE standard C57.104. Once the result of the method is defined as uncertain, this method does not work properly. But in this uncertain case, the Rogers ratio method works properly. In the field of the fault diagnosis of electrical distribution foundations or companies, there is some contradiction with the IEC ratio method in terms of the ratios r1, r2, and r3. From the ratios of IEC method, the operator easily interprets the fault types which are mainly thermal and electrical stress. However, because of the very close value between ratios, it may cause improper transformer fault interpretation so that the electrical distribution system faults is not fixed. It is totally 10 faulty cases in IEC ratio method that leave an undetermined status. Practically, the undermined status may include several issues, so it has electrical or thermal faults with different low and high temperatures. The weak point of the IEC ratio method is not to define the undetermined cases [2], [18], [19].

The DTM method estimates the DGA data through a graphical representation. The Duval triangle has seven fault zones. It uses the concentrations of the relative % values of CH4, C2H2, and C2H4 on the sides of the triangle. To define Duval triangle method fault classification, the weak point of the DTM method is not to define the boundaries of the fault types. For example, the PD and T1 fault types are very close to each other due to the neighbouring. When the values of released gases are on these limits, the traditional Duval triangle method could not respond to the transformer oil error of DGA [3], [20], [21]. The coordinates of the triangle can be calculated using (1)–(3):

$$\%C2H2 = 100 \times x \div \left(x + y + z\right), \tag{1}$$

$$\%C2H4 = 100 \times y \div \left(x + y + z\right), \tag{2}$$

$$\%CH4 = 100 \times z \div \left(x + y + z\right),$$
$$x = (C2H2),\ y = (C2H4),\ z = (CH4)\ in\ ppm. \tag{3}$$

The Duval triangle method allows for the identification of six basic fault types, as well as electrical/thermal fault mixtures in the DT region. The flow chart of the Duval triangle method includes the fault zone boundaries of %CH4, %C2H4, and %C2H2. There is no undetermined case in the Duval triangle method. However, the parameters of the Duval triangle method are p1, p2, and p3, which has a greater limit than IEC ratio method parameters. Smaller limit rates are not used in the Duval triangle method so that there are no undetermined cases [4], [22]–[24].

The important gases which are H2, C2H6, CH4, C2H4, and C2H2 are implemented as input parameters in the Duval Pentagon method. The order of the gases in the five peaks of the Pentagon method corresponds to the increasing energy or temperature of the faults that produce these gases (from H2 to C2H2). In this method, six basic fault types (PD, D1, D2, T1, T2, and T3) are considered, and as in the Duval triangle method, these fault types can be detected with the Duval Pentagon [25]–[27]. This method is mainly based on the IEEE C57.104 standard. This method can identify three faults (PD, TD, D2). There are four ratios that are, respectively, r1, r2, r3, and r4 in the Doernenburg method. There are some ambiguous points of the Doernenburg method, which are called fault not identificable. In these points, the exact solution of a fault type is not interpreted in terms of thermal and electrical factors. If there is no fault status in the transformer, the Doernenburg method could detect this desired status. However, in practise, although there is no fault for this method calculations, the transformer has the problem of cellulose paper degradation in the transformer because the combustible gases are released. Finally, the limit parameters of the Doernenburg method get small values between 0.1 and 1.1 [5], [28], [29].

The key gas method (KGM) uses singular concentrations of six fault gases (H2, CH4, C2H6, C2H4, C2H2, CO) to detect transformer faults. There are some limits that have normal state ranges and abnormal and critical threshold values of gas parameters in the key gas. When the C2H4 gas released exceeds 50 ppm concentration, there could be a thermal fault in the transformer oil. When the hydrogen gas being released exceeds 100 ppm concentration, there could be a low-energy partial discharge fault in transformer oil. When the methane gas released exceeds 120 ppm concentration, there could be an arching fault in the transformer oil. When the carbon monoxide gas released exceeds 350 ppm concentration, there could be cellulose fault in transformer oil. When the ethylene gas released exceeds 50 ppm concentration, there could be a thermal fault in transformer oil. When the acetylene gas released exceeds 35 ppm concentration, there could be a thermal fault in transformer oil [6], [30], [31]. Similarly to DRM, Rogers ratio method (RRM) is based on the IEEE C57.104 standard, but only considers three rates: Rate 1, Rate 2, and Rate 5. RRM is an efficient method when each gas concentration passes the limit rate. There are totally six cases that are, respectively, Case 0 to Case 5. Like the IEC ratio method, the Rogers ratio method sometimes gives an undetermined case. These undetermined cases recurred three times in the flowchart. However, in practise, although there is no fault for this method calculations, the transformer has the problem of cellulose paper degradation and arching in the transformer because the combustible gases are released. Finally, the limit parameters of the Rogers ratio method get small values between 0.1 and 3 [32]–[34].

The nomograph method is a traditional method that is mainly modified by a key gas method. It facilitates the interpretation of fault gas data by presenting the error graphically. In particular, the concentration ratios of released ethane and methane gases are presented logaritmically in the nomograph method. The nomograph method gives the researcher three statuses about the transformer which are warning status, normal status, and caution status. There is a challenge for this method, which is called an excessive threshold value. This case means that the fault type is not detected where the link point spots above a threshold value in the logarithmic representation [10], [35]–[37].

The low-energy degradation triangle method is another traditional method that is mainly modified by the Duval triangle method. This method includes the poor energy dissolved gases H2, CO, and CH4 excluded in the triangular representation. The C2H6, C2H4, and C2H2 produced by high-energy decay in this method are inappropriate indicators of low-energy decay. Instead, the dissolved gases produced in paper and oil during low-energy degradation processes should be used in the low-energy indicator: H2, CH4, and CO. The crucial factor of the low-energy degradation triangle method is named properly as the insulation degradation identification. When deep high-energy surroundings occur because the arcing fault, it can be easily said that there are greater hydrogen amounts with diminished methane-carbon monoxide amounts. When the hydrogen gas is released, the heat energy inside the transformer increases. Also when CH4 is released, oil degradation occurrs [7], [38], [39].

Comparison and Inconsistencies of Classical Methods. It can be seen from the fault prediction accuracies obtained from the studies that not every classical DGA method gives 100 % accuracy. When the classical methods are inspected in terms of their fault diagnosis accuracy, there will be seen some crucial disadvantages specially defined as listed below.

1. Since the results obtained from these methods do not include algorithm-based programming or comprehensive mathematical calculations, they have a serious disadvantage in terms of accuracy and consistency

estimation compared to algorithm calculations made with artificial intelligence techniques.
2. These methods cannot distinguish situations where more than one electrical or thermal fault occurs simultaneously.
3. Even if traditional methods use the same dataset, it has been observed that they provide conflicting accuracy below 60 % when their accuracy classes are compared.
4. All custom DGA methods are easy to apply while the cases of inaccuracy and instability are not resolved [29]–[120].

III. Historical Backround for Development of the Devices Used

Currently, there are two types of devices called infrared and gas chromatography. These devices are frequently used in the online or offline monitoring of gas values in light of the information obtained from studies in the literature on the detection of very small gases at the ppm level in transformer oil. Some important and detailed information about these devices is defined as below.

1 - Infrared: Infrared (IR) sources, optical filters, photoacoustic cell, lock-in amplifier are used in photoacoustic spectrometry (PAS) detection system as functionality.

PAS is defined as a sample gas detection. This sample is a new technique that has the absorption spectrum of substances. The PAS is used for many sectors related to the optoelectronics industry. Using PAS can overcome the shortcomings of traditional gas detection technology, effectively improve test accuracy, and reduce the maintenance cost [108], [109], [120], [121]. Nondispersive infrared sensor (NDIR) measures electro-optically absorbed wavelengths in the infrared. Small changes in the intensity of the lamp or the efficiency of the optical elements reduce the signal, as if it were absorbed by the gas. As transformer oil ages and additional by-products form, interference in the absorption spectrum, which is particularly problematic, also reduces the signal. The H2, O2, and N2 gas values cannot be detected with the NDIR monitoring method. The principle of the Fourier transform infrared spectroscopy (FTIR) technique is fundamentally described as passing through different gas concentrations; gas sensors, and central process unit are the main parts in FTIR [122], [123].

In terms of qualitative detection, the FTIR device is stable. However, in terms of by temperature, pressure, vibration factors, the quantitative analysis is badly affected. The combination of FTIR and PAS is very useful for ensuring sensitivity. FTIR and PAS combination diagram is shown in Fig. 1 [124]–[126].

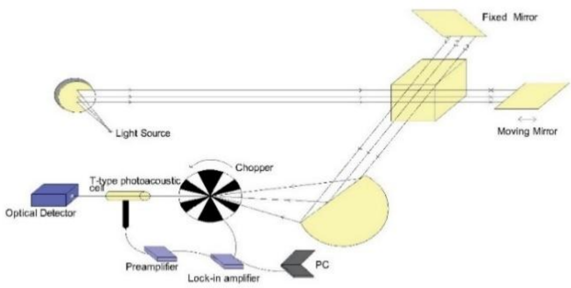

Fig. 1. FTIR and PAS combination diagram.

2 - Gas chromatography: As stated in the IEC 60567 standard, the gas chromatography monitoring method has high accuracy and consistency rates. However, there are some disadvantages that include the exhaustion of a large amount of carrier gas and the regular replacement of the chromatographic column. Therefore, many high-tech gas detection techniques have been searched for in this issue by related companies. It is known that the leading advanced DGA measuring devices from international brands generally design hardware and software according to this method. The success of this design directly depends on the success of the detector sensor that can detect key gases. The sample DGA collection is shown in Fig. 2 [127]–[129].

Fig. 2. Sample DGA data gathering for the online chromatographic monitoring system of transformers [95].

IV. Methods for Artificial Intelligence Techniques in Dissolved Gas Analysis

Artificial intelligence techniques are explained in detail under the heading “Individual and Hybrid artificial intelligence techniques” [130]–[133].

Today, when applying the recommended artificial intelligence (AI) techniques for transformer fault diagnosis, gas concentration values in the ppm range obtained from the field and literature and the ratios obtained from these values are used in the data collection and storage stages, normalisation for the purpose of data cleaning, data modelling, and meaningful conclusions drawn from the data. Respectively, the optimisation stages are defining the data, preparing the data, selecting the machine learning algorithm, training algorithm, evaluating the model, deploying, predicting, evaluating the prediction, and final precise. The process steps for machine learning are data collection and storage, data cleaning and analysis, modelling, optimisation.

When classification methods are making, there is an important issue which is called the confusion matrix, which is shown in Fig. 3. For researchers, to analyse the accuracy of the fault diagnosis method, a confusion matrix is necessary to get inside the calculations. The test set in the confusion matrix includes the true values. The confusion matrix table is presented to show the correct and incorrect classification predictions. The benefits of artificial intelligence methods are, respectively, consistency, accuracy, and detection ability compared to traditional methods.

For the second equation (5), consistency is the average of the SFn of all errors of a method. The accuracy of the method for the third equation (6) is the portion of lucrative predictions among cases where the results are not "No Result" in the method, while the detection ability of a method is the percentage of successful predictions among all cases and is calculated by the fourth equation (7). By the way, the flow chart of artificial intelligence algorithm optimisation process includes, respectively, sample collection station, data transformation approaches, semi-supervised learning approaches, selection of suitable classifier, initialisation of hyperparameter, whale optimisation algorithm, tuned hyperparameter, recognition rate [134]–[138].

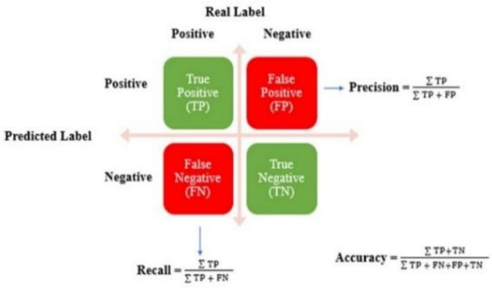

Fig. 3. Prediction accuracy rates with confusion matrix [43].

Equations (4)–(7) have some definitions: SFi is the percentage of lucrative predictions of a given fault type Fi, PFi is the # of successful predictions for the first equation, and n is the number of faults detected by the method:

$$S\ Fi = \frac{P\ Fi}{\#\ of\ \ cases\ of\ \ with\ Fi\ \ fault}, \tag{4}$$

$$Consistency = \frac{\sum_{i=1}^{n} S\ Fi}{n}, \tag{5}$$

$$Accuracy = \frac{\sum_{i=1}^{n} P\ Fi}{Total\ Cases\ without\ \ No\ result\ case} \times 100, \tag{6}$$

$$Detecting\ \ Ability = \frac{\sum_{i=1}^{n} P\ Fi}{Total\ Cases} \times 100. \tag{7}$$

General AI algorithms have some deficiency that is described as the ability to deal with inconsistencies in a training dataset. Parameter optimisation is very important for all artificial intelligence techniques, especially support vector machine (SVM) [139], [141]. As shown in Fig. 4, it represents the strength of the neuron weights that includes bias nodes, input nodes, and output nodes.

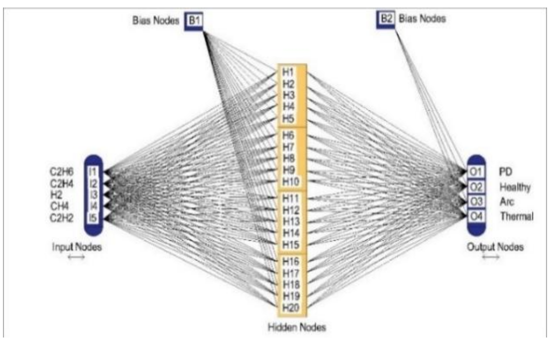

Fig. 4. The strength of the neuron weights for artificial neural networks.

There still looks a big problem which is called imbalance datasets in DGA. This problem may be one of the main difficulties in identifying errors. To overcome these issues, a generative adversarial network (GAN), Control, and synthetic minority oversampling technique (SMOTE) models are mainly used as balancing data. The accuracy of the method by collecting models is presented in Table I.

TABLE I. OVERALL ACCURACY FOR THREE CLUSTERING MODELS.

	Rate (%)		
Error Sorts	**Control**	**SMOTE**	**GAN**
Low discharge	91.76	84.23	82.8
Low discharge with thermal fault	49.38	75.31	83.9
Thermal fault at low temperature	56.00	78.67	86.6
High discharge	96.56	89.31	88.1
High discharge with thermal fault	27.78	68.52	77.7
Thermal fault at high temperature	95.75	87.26	88.0
Partial discharge	18.18	54.55	77.2
Thermal fault at medium temperature	**95.90**	**84.43**	**85.2**

Once DGA dataset is used as crucial predictions for machine learnings, wavelet LS-SVM regression (W-LSSVM) and mutation with particle swarm optimization (PSO) are important to get better accuracy in machine learning techniques. To obtain end prediction results by optimising, the raw datasets are data, preprocessing, training, optimisation, evaluation, testing, forecasting. When parameter optimisation flowchart is discussed, the PSO in the W-LSSVR method consists, respectively, of fitness evaluation, training, cross validation, updating, mutation, termination check, hyperparameters optimisation. When we look at the type of software that the technique uses, we have MATLAB software [142] Six data preprocessing methods (SMOTE) are proposed to solve this problem. In the study conducted by Wang the new hybrid algorithm was used that includes random undersampling (RUS), adaptive synthetic sampling approach (ADASYN), borderline synthetic minority oversampling technique (B-SMOTE), edited nearest neighbour (SMOTEENN), and conditional generative adversarial (CGAN). The diagnostic accuracy of different underlying machine learning methods for different faults is very different. Imbalance in sample datasets is frequently observed in DGA, which has become one of the main challenges for accurate fault diagnosis. To address these problems, a generative adversarial network (GAN) model is proposed to perform data augmentation.

The contribution of data balancing in back propagation neural network (BPNN), SVM, and deep belief network (DBN) to prediction accuracy is shown in Figs. 5–7.

Once the data growth procedure is performed, the fault identification accuracies of the BPNN, SVM, and DBN methods were implemented, respectively, as an average of 30 %, 25 %, and 50 % [143] The accuracy of the method is presented in Table I. Since the DGA-based transformer fault data are complex and the value difference is large, all data should be normalised. The results show that hybrid enhanced grey wolf optimisation (HIGWO) has better optimisation performance and significance. The procedures to obtain final prediction results by optimising the raw dataset are, respectively, data, preprocessing, training, optimisation, evaluation, testing, and forecasting. The parameter optimisation flowchart using PSO in W-LSSVR includes, respectively, fitness evaluation, training, cross validation, updating, mutation, termination check, and hyperparameter optimisation [144], [145].

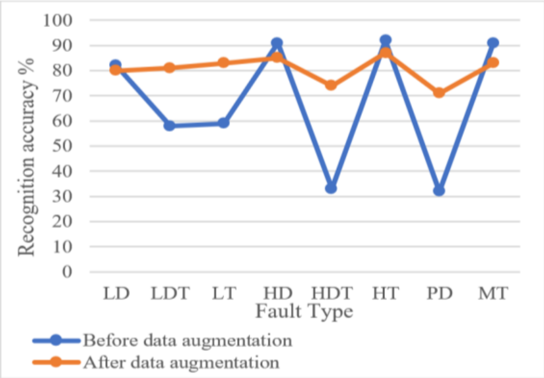

Fig. 5. Contribution of data balancing to prediction accuracy in BPNN.

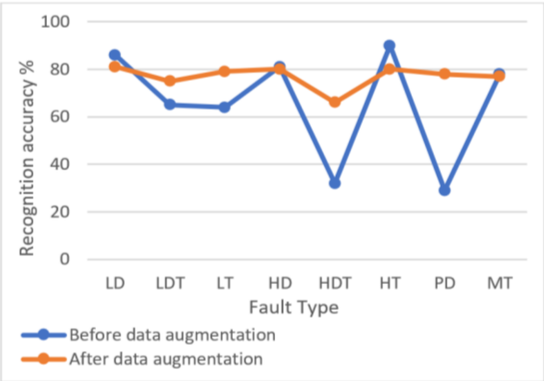

Fig. 6. Contribution of data balancing in SVM to prediction accuracy.

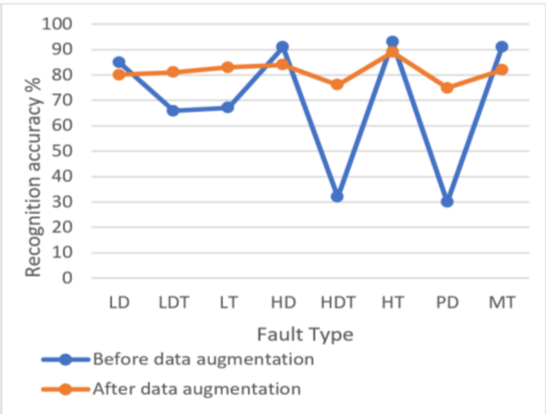

Fig. 7. Contribution of data balancing in DBN to prediction accuracy.

Because the specifications of the DGA data are volumed values and complex, all these data require a normalisation process. The oil-filled transformer chromatographic data are used as input for the normalisation. Then, each fault type is get as a machine learning output. When SVM parameter optimisation is performed, PSO, GWO, GA and MGWO are applied in the optimisation process to get a better accuracy rate. To obtain better accuracy of transformer fault, the GWO algorithm is used in the algorithm. The results indicate that enhanced GWO has better optimisation performance and significance [146], [147].

Compared to modified kernel extreme learning machine-grey wolf optimizer (MGWO-KELM), AdaBoost-IPSO SVM, and EDPFA BP neural network diagnostic methods, diagnostic accuracy is better than the other three methods [148].

Individual and Hybrid Artificial Intelligence Techniques. Artificial intelligence applications are generally divided into two groups that are hybrid and individual techniques [43]–[247].

For Studies with the Support Vector Machine (SVM) Method, Jing, Jia-dong, and Yong-zhe [52] presented a method of hybrid intelligent algorithm of immune support vector machines to improve the diagnostic accuracy of power transformer fault. Baker, Nese, and Dursun [66] proposed a model that has both fuzzy logic and SVMs. The model results are over 94 %. Wu, Sun, Zhang, Zhong, and Cheng [91] proposed the method using SVM. Illias, Choon, Liang, Mokhlis, Ariffin, and Yousof [96] proposed that SVM, one of the artificial intelligence techniques, be applied to determine the type of power transformer fault based on DGA data. Misbahulmunir, Ramachandaramurthy, and Thayoob [102] proposed a model that is based on SVM using a self-organising map. Zhang *et al*. [106] discussed that a series of new combinations of DGA features were selected as input from the mixed amount of DGA features and an optimised SVM transformer fault diagnosis model has been established by an improved krill swarm (IKH) algorithm. Zhang, Peng, Fang, Zhao, Li, and Liao [109] presented a model based on SVM using optimisation of quantum behaved PSO. Malik and Mishra [120] used the proximal SVM (PSVM) to identify the types of fault initiation. Illias, Chan, and Mokhlis [182] proposed hybrid feature selection-(AI-GSA) techniques with the SVM technique have been successful for DGA in identifying the type of power transformer fault. Fei and Zhang [183] proposed a genetic algorithm SVM (SVMG) to diagnose power transformer faults, where the genetic algorithm (GA) was used to select the appropriate free parameters of the SVM. Wei, Tang, and Wu [189] discussed the SVM artificial intelligence technique using PSO parameter optimisation. Tan, Guo, Wang, and Wan [209] proposed DGA-based semi-supervised two-stage diagnostic system with mutated SVM to complete the online monitoring and diagnosis system of power transformers using fewer labelled samples. Wang [224] proposed an improved SVM with diagnostic accuracy of the K-mean algorithm. The accuracy obtained in the study was 98.4 %. Yang, Qin, Pang, and Huang [92] proposed SVM that has average accuracy and is shown in Fig. 8.

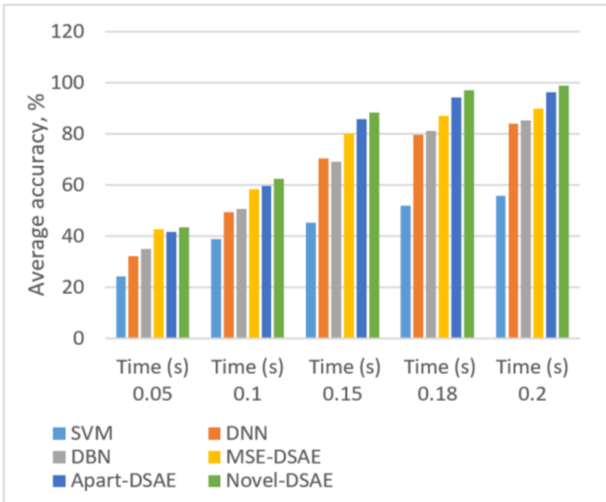

Fig. 8. Average accuracy for several ML techniques.

Rao, Fofana, Rajesh, and Picher [148] presented SVM to classify the fault of the power transformer. The overall accuracy is presented in Fig. 9.

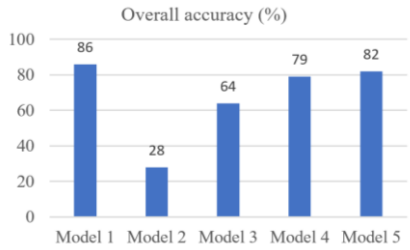

Fig. 9. Average accuracy for five ML techniques.

The proposed hybrid feature selection techniques of Mokhlis AI-GS with the SVM technique have been used successfully by DGA to identify the type of power transformer fault [182]. Zhang, Sun, Hou, Li, and Liu [193] proposed the combined model based on improved information entropy and uncertain support vector machine (IVSVM) was incorporated into transformer fault diagnosis using oil-dissolved gas analysis (DGA). Overall accuracy is presented in Fig. 10.

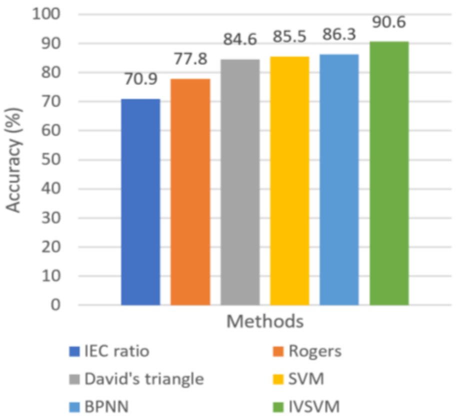

Fig. 10. Overall accuracy.

Hu, Mo, Ruan, and Zhang [222] proposed a new dissolved gas analysis method to improve the accuracy of transformer fault diagnosis. The slime mould optimised SVM (SMA-SVM) and the logarithmic arctangent transform (LOG-ACT) are combined. Wang [224] proposed an improved SVM with K-mean algorithm diagnostic accuracy. The accuracy obtained in the study was 98.4 %. Ding, Ding, Wang, and Zhou [227] proposed a transformer fault diagnosis method using an optimised SVM by an improved sparrow search algorithm (ISSA). The overall accuracy is presented in Fig. 11.

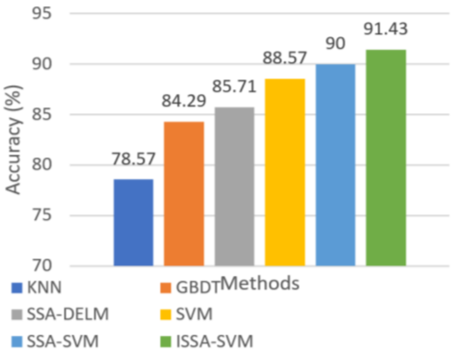

Fig. 11. Overall accuracy.

For Studies with Fuzzy Logic (FL), Malik, Sharma, and Naayagi [75] proposed a comprehensive three-stage fuzzy logic approach to emulate industry best practices for benefits such as time and cost savings. Su [113] presented a new fuzzy logic technique that uses four gas ratios in fuzzy logic analysis. The overall accuracy is presented in Fig. 12. Zhao and Yun [134] proposed a fault diagnosis method that combines fuzzy logic with FL, cerebellar model articulation controller (CMAC) neural network to improve the accuracy of fault diagnosis. Jing, Zhang, and Yang [154] proposed a self-learning adaptive classifier based on the fuzzy reinforcement learning algorithm for transformer startup fault.

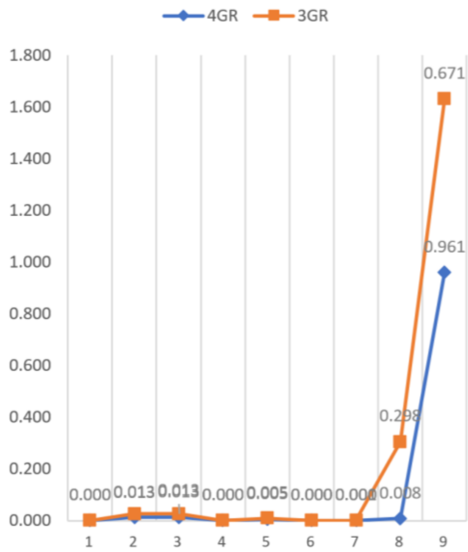

Fig. 12. Overall accuracy.

For Studies with the Ordered Ant Miner (OAM) Classifier, Satyanarayana, Reddy, Govindan, Mandlik, and Ramu [43] presented the application of the OAM classifier by comparing it with the IEC ratio method for the prediction of relevant failure. The ant miner technique has been shown to be a very effective method for fault detection in transformers.

For Studies with Artificial Neural Network (ANN) Classifier, Qiping, Wude, and Zhida [51] introduced the new intelligence technology in the transformer fault diagnosis-artificial intelligence system (TFDAI). Yu and Zang [53] proposed a model composed of a rough set theory. Illias and Chai [56] presented a model that has both a neural network and a modified PSO technique to determine the fault type in the power transformer insulation system. Nagpal and Brar [58] discussed the diagnosis of multiple faults which failed in some cases because the DGA results could not be matched to the existing fault codes. To overcome this problem, the use of neural networks was proposed to highlight their ability to detect incipient faults in the transformer. Poonnoy, Suwanasri, and Suwanasri [59] discussed an artificial neural network called the Levenberg Marquardt backpropagation training algorithm as a multilayer inverse diffusion. Salami and Pahlevani [60] discussed artificial ANN applications for the diagnosis of power transformer initial fault. Yang and liang [65] developed a combined artificial neural network and expert system tool (ANNES) for the diagnosis of transient transformer faults using oil DGA. Enriquez, Lima, and Saavedra [104] discussed parameter optimisation with binary particle swarm optimization (BPSO) ANN and k-nearest neighbours network (KNN) classifiers. The assertiveness of the proposed approach was evaluated on two classifiers with satisfactory results. Malabanan and Nerves [121] used a combined artificial immune system (AIS) and ANN called the immune neural network as an alternative approach to evaluate transformer condition to address the limitations of traditional methods. Demirci, Saka, Gozde, Dursun, and Taplamacioglu [176] used multilayer perceptron neural network, SVM, and Naive Bayes classifiers for fault diagnosis.

For Studies with an Artificial Immune Network Classification Algorithm, Hao and Cai-xin [45] proposed an artificial immune network classification algorithm (AINC) inspired by the innate immune system, which can respond to an almost unlimited number of foreign pathogens to improve the ability to interpret the result of DGA [47].

For Studies with the KNN Algorithm, Wang, Littler, and Liu [47] present a comparative study of ANN, SVM, and KNN and decision tree models using the created database. Kherif, Benmahamed, Teguar, Boubakeur, and Ghoneim [97] investigated oil-immersed power transformer fault diagnosis using different DGA methods using a database set of 501 samples. A decision tree algorithm was developed in the KNN classifier to improve the accuracy of transformer fault diagnosis. Das, Paramane, Chatterjee, and Rao [144] discussed the effect of balancing unbalanced DGA data. The average accuracy is presented in Fig. 13.

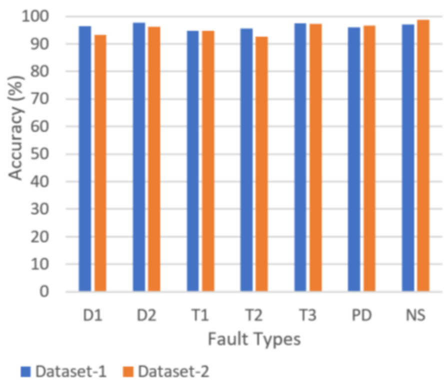

Fig. 13. Average accuracy.

For Studies with Decision Tree (DT), Menezes, Araujo, Almeida, Barbosa, and Braga [90] proposed decision tree (DT) as a possible solution to overcome traditional performance problems. Raj, Venkatachary, and Andrews [174] performed a classification using a DT. The data are trained using supervised machine learning (SML). The accuracy of the predicted data using DT and optimised DT is 62.9 %.

For Studies with Backpropagation Neural Network (BPNN), Yin, Zhen, Huo, and Chen [48] discussed that BP builds a fault diagnosis model and uses the resulting fault instance data to complete model training and testing. The average accuracy is presented in Fig. 14. Shoupeng *et al.* discussed that the optimised BP neural network algorithm is compared with the traditional BP neural network algorithm. The simulation results show that the GA-optimised neural network model can play a better role in transformer fault diagnosis. Feng and Bo [61] proposed a method for diagnosing transformer faults using ANN. Zheng, Liu, and Lu [129] used the traditional BP network for transformer fault diagnosis. In the study, the accuracy rate reached 85 %. Hao, Tao, Rui-jing, Jian, and Cai-xin [137] discussed that the prediction results obtained with the work done with BPNN were compared by considering the fuzzy c-means (FCM) algorithm, whose cluster analysis has attracted a great deal of attention recently. Zhong, Tang, Peng, and Zhang [140] presented a quantitative spectral analysis of dissolved gas based on the parallel BPNN method.

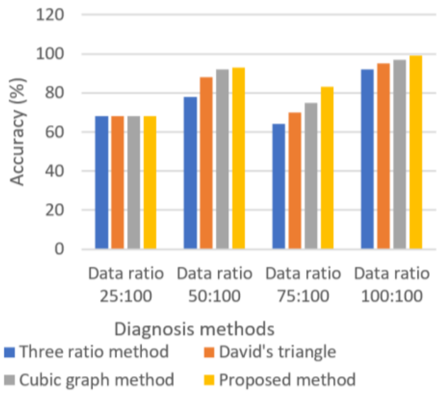

Fig. 14. Average accuracy.

For Studies with Random Forest (RF), Gao, Gao, Yang, Feng, Song, and Li [85] discussed the membership function of the DGA based on the state evaluation criterion, and the membership degree of each DGA parameter was calculated as a new feature parameter. Wang *et al*. [86] discussed the situation where transformer data is generally an unbalanced dataset, leading to supervised learning models that focus more on a wider variety of examples, resulting in decreased model performance. Patil, Patil, Dharme, and Jarial [160] discussed learning algorithms such as the KNN classifier, logistic regression, the Naive Bayes classifier, DT Classifier, and the ensemble learning algorithm to detect faults in power transformers by analysing gases dissolved in transformer oil. Haque, Jamshed, Chatterjee, and Chatterjee [170] considered the RF classifier. The prediction accuracy was high with 91.45 %. Rediansyah, Prasojo, Suwarno, and Abu-Siada [49] used seven artificial intelligence models. Overall accuracy is presented in Fig. 15.

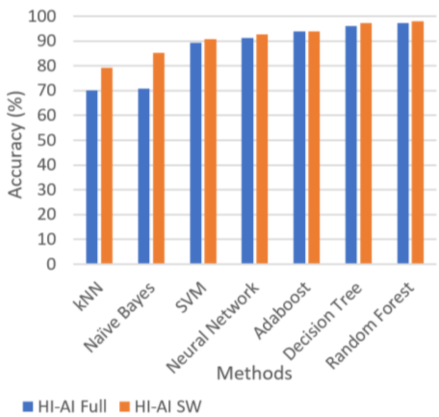

Fig. 15. Average accuracy.

For Studies with a Deep Neural Network, Mehdipour Picha, Bo, Chen, Rana, Huang, and Hu [55] proposed the use of a deep neural network to determine the type of transformer fault. Kim, Park, Kim, Jo, and Youn [178] proposed a new framework called BDD, which combines Duval's method with the deep neural network (DNN) approach for diagnosing power transformer faults using DGA. The proposed BDD approach achieved a high accuracy of 95.4 % as shown in Fig. 16.

For Studies with the Radial Basis Function (RBF) Neural Network, Chao, Hong, Yang, and Ye [57] presented a model that is based on the RBF neural network and clustering. Morais and Rolim [139] used general regression neural network (GRNN), a type of neural network based on radial basis function (RBF).

For Studies with Cognitive Artificial Intelligence (CAI), Yaqin and Khayam [62] examined the method of cognitive artificial intelligence (CAI), which is artificial intelligence that can mimic the human brain's ability to build knowledge cultivation systems (KGSs). As a result, the accuracy of CAI shows 91.67 %.

For Studies with Extreme Learning Machine (ELM), Malik and Mishra [67] discussed principal component analysis using RapidMiner software applied to IEC TC10 and related datasets to identify the most relevant input variables for incipient fault classification. Yang, Yin, Jia, and Yue [151] addressed the shortcomings of the extreme learning machine (ELM), such as poor training stability and low training accuracy. To optimise ELM, Hunter recommends a transformer diagnostic method through the prey optimiser (HPO). Chen, Zhang, and Chen [164] discussed that although the multiclass imbalance problem is difficult in terms of algorithm development, this issue is underestimated due to the fact that the highly imbalanced dataset is not investigated. Li, Hai, Feng, and Li [169] proposed a transformer fault diagnosis method based on optimisation of kernel parameters and weight parameters of a kernel extreme learning machine (KELM). The average accuracy is presented in Fig. 17.

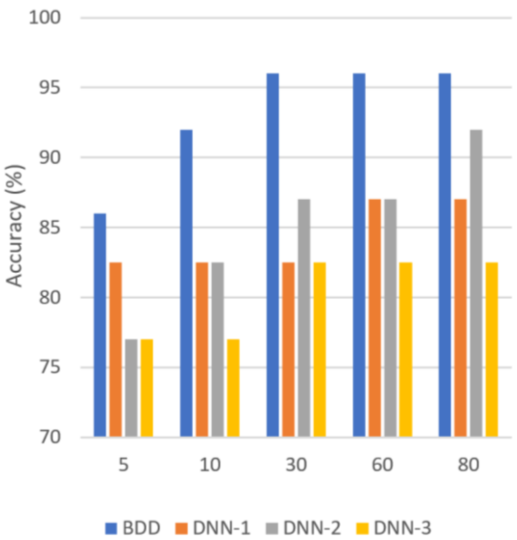

Fig. 16. Average accuracy.

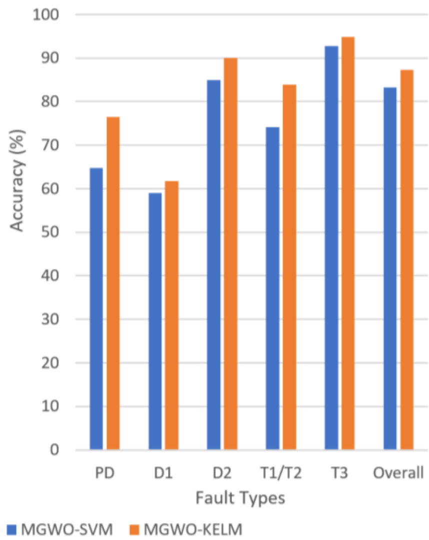

Fig. 17. Average accuracy.

For Studies with the Rough Set (RS) Algorithm, Li, Huang, Wang, and Tang [119] presented a new power transformer fault diagnosis method based on rough set theory (RST) and an improved artificial immune network classification algorithm. Xiaoqing, Juemin, Yingwei, and Bo [127] proposed a model based on RST integrated with artificial fish shoal algorithm (IAFSA) for transformer fault diagnosis.

For Studies with Dempster-Shafer (D-S) Theory, Yang, Yue, Jia, and Sun [74] used extreme learning machines (ELM) as input for BP neural networks and SVMs. Bhalla, Bansal, and Gupta [180] proposed DST. This method has been successfully used to identify the type of fault that develops in a transformer, even when there is conflict in the results of AI techniques applied to DGA data.

For Studies with Genetic Algorithm (GA), Nanfak, Eke, Meghnefi, Fofana, Ngaleu, and Kom [76] presented hybrid type using the GA and evolutionary k-means clustering algorithm. In fact, with the proposed method, the best performance was achieved at 98.29 % compared to other models in the literature.

For Studies with Improved Golden Jackal Optimisation (IGJO) based on Stochastic Configuration Networks (SCNs), Lu, Shi, Fu, and Xu [78] proposed the simulation results that show that the optimisation of the parameters of the SCN using the IGJO algorithm can effectively improve the accuracy of the transformer fault diagnosis by 96.11 %.

For Studies with an Adaptive Neuro-Fuzzy Inference System (ANFIS), Jan, Rahman, Parveen, and Khan [79] used ANFIS to apply a multistage binary classification scheme to diagnose incipient errors. It has been shown to significantly increase diagnostic accuracy by 82.10 % compared to its traditional counterparts. Aghaei, Gholami, Shayanfar, and Dezhamkhooy [196] discussed ANFIS. The error trend is presented in Fig. 18.

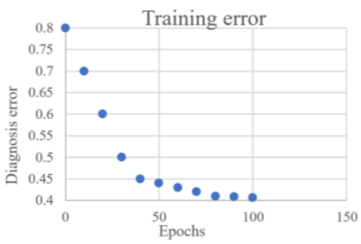

Fig. 18. The trend of the training error via epochs.

For Studies with Multilayer Perceptron (MLP), Vidal and Castro [80] used MLP to eliminate the imbalance in the data in the database and therefore improve the generalisability of the classifier. Xu, Li, Wang, Zhao, and Xie [186] proposed MLP for intelligent diagnosis of power transformer faults. High prediction accuracy is achieved. Wang, Littler, and Liu [81] proposed a dynamic fault prediction approach using a long short-term memory (LSTM) model with intelligent classification to determine the operating state of a transformer to predict and prevent potential transformer damage. Baiju and S [83] proposed a new method that combed stack denoising autoencoder and bidirectional long short-term memory (SDAEBiLSTM) to achieve greater diagnostic sensitivity.

For Studies with Adaptive Synthetic Sampling Approach (ADASYN), Rajesh, Rao, Fofana, Rozga, and Paramane [82] proposed ADASYN, an oversampling method that generates synthetic examples for minority classes, balances the dataset, and improves classification accuracy.

For Studies with the Chaotic Arithmetic Optimiser Algorithm (CAOA), Yan, Zhang, Duan, Wang, Zhao, and Wang [87] used the arithmetic optimiser algorithm, a metaheuristic based artificial intelligence tool.

For Studies with Adaboost.C2-Classification Tree (AM-CT2) Ensemble Model, Ru, Zhang, Yang, Zou, Lu, and Xu discussed AM-CT2 to increase the accuracy of transformer fault diagnosis in developing unbalanced datasets. Xu, Li, Wang, Zhao, and Xie [186] discussed advanced broad learning system (BLS) and easy ensemble learning methods.

For Studies with Gaussian Process Multiclassification (GPMC), Wang, Littler, and Liu [95] proposed a GPMC method. The accuracy of the different methods is presented in Table II. E., Zhang, He, Zhang, Cao, and Lv [172] used an evidential model with reference points in the form of a Gaussian distribution optimised by a constrained genetic optimisation algorithm (GA).

TABLE II. ACCURACY OF DIFFERENT METHODS.

Method	Accuracy (%)
Doernenburg ratio	79.0
IEC	42.4
Key gas	37.8
SVM	94.3
ANN	92.3
KNN	94.2
Decision Tree	93.7
LR	88.0
GPMC	**95.4**

For Studies with an Optimum Path Forest (OPF), Souza, Ramos, Gastaldello, Nakamura, and Papa [128] proposed a fast and accurate method for fault diagnosis in power transformers through the OPF classifier. Experiments showed that OPF can achieve high recognition rates at low computational cost.

For Studies with Naïve Bayes (NB), Prasojo, Azizi, Kurniawan, Suwarno, Sutikno, and Ridzki [157] used a dataset containing DGA data with known real fault from power transformers to verify the effectiveness of the model created using NB. The accuracy among six machine learning models is shown in Fig. 19.

For Studies with Explainable Boosting Machine for Transformer Fault Diagnosis (EBMT), Liao, Zhang, Cao, Ishizaki, Yang, and Yang [161] proposed a method, including traditional glass-box models (e.g., LR, DT, and GAN and advanced black-box models. Compared with popular (RF, XGBoost, MLP, CNN, and LSTM-KNN) benchmarks.

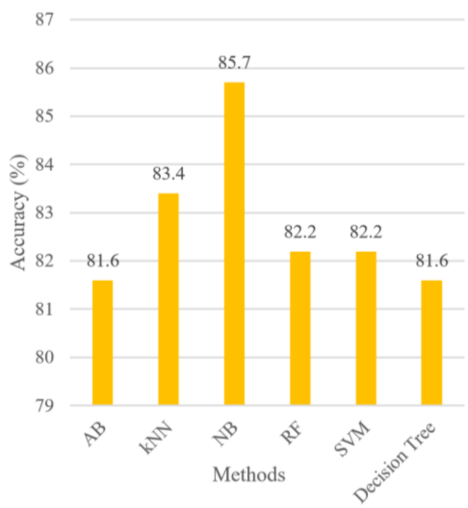

Fig. 19. Average accuracy.

For Studies with Quantitative Descriptive Analysis (QDA), Saroja, Haseena, and Madavan [165] proposed QDA to classify transformer faults with a high accuracy of 99.29 %.

For Studies with the Temporal Convolutional Network (TCN) and Graph Convolutional Network (GCN), Luo *et al*. [166] presented a prediction method based on TCN and GCN for the dissolved gas content in transformer oil. Yang, Fang, Zhang, Tang, and Hu [210] proposed two models. In order to investigate the nonlinear and nonstationary properties of the gas content, a honey badger algorithm-variational mode decomposition-temporal convolutional network (HBA-VMD-TCN) univariate decomposition prediction based on the Honey Badger algorithm, variable mode decomposition, and time convolutional network (TCN) is established.

For Studies with Radial-Based Oversampling (RBO), Zhang, Sheng, Hou, Zhou, and Jiang [214] proposed a new method called RBO.

For Studies with the Refined Deep Residual Shrinkage Network (Refined-DRSN), Hu, Ma, and Shang [226] proposed a method so that the recognition accuracy results is greater than 99 %.

V. CONCLUSIONS

Traditional transformer fault diagnosis methods have limitations such as the inability to detect hidden faults within the transformer in a timely manner, the difficulty in accurately detecting fault types, and the inability to formulate appropriate revision strategies. The most important disadvantage of these methods is that they cannot distinguish situations where more than one electrical or thermal fault occurs simultaneously. Therefore, performing fault diagnosis based on artificial intelligence methods in transformers is of great practical importance. One of the problems encountered in artificial intelligence methods is cost, which is one of the basic economic issues. For this reason, the optimum path forest classifier was used to reduce the high cost and was found to provide strong prediction results. In this study, firstly, the results obtained from more than one traditional method for error estimation are compared. In this comprehensive review, the historical development of the main devices used in dissolved gas analysis (DGA), including gas chromatography, photoacoustic spectrometry (PAS), and NDIR, is discussed. The gas chromatography monitoring method specified in the IEC 60567 standard stands out with its high accuracy and consistency rates, despite its cost disadvantages.

Studies based on artificial intelligence have been extensively examined. First, the researchers have determined that there are some difficulties in obtaining the dataset source consisting of dissolved gas concentrations, which are the input parameters in these studies. Although some studies took datasets from a power transformer in the field, some studies used datasets available in the literature. In this context, it is thought that recording, storing, and encrypting the measurement results on a regional or international basis in accordance with a certain format by the relevant country organisations and providing access to the data to nationally or internationally authorised researchers will contribute significantly to more accurate and ethical estimation results in future studies. Secondly, based on two performance measures such as accuracy and calculation time, it can be concluded that the artificial intelligence techniques for the proposed multistage fault diagnosis of power transformers using DGA data outperform traditional methods. Support vector machine (SVM), fuzzy logic (FL), Naïve Bayes (NB), and artificial neural network machine learning (ANN ML) are frequently discussed in the literature today due to their satisfactory performance with high accuracy and fast calculation time.

General artificial intelligence (AI) algorithms lack the ability to handle inconsistencies in a training dataset. Parameter optimisation is very important for all artificial intelligence techniques, especially SVM. Therefore, it is recommended to apply the optimisation method to artificial intelligence methods to obtain better accuracy results. When feature selection is not made, training data are reduced, and test data are increased, artificial intelligence algorithm accuracy decreases. In the literature, it has been determined that in most studies incorrect conclusions are reached by neglecting parameter optimisation and directly comparing the results obtained from the proposed technique with methods with relatively lower accuracy. In the future, the accuracy of fault prediction should be improved by adding more training data and selecting the optimum parameter, with research aimed at improving the quantity and quality of the data. In the studies carried out, particle swarm optimisation (PSO), genetic algorithm (GA), ant colony, kernel principal component analysis (KPCA), AM2-, and other data-based artificial intelligence method parameter selections such as SVM, decision trees, KNN, and even deep learning. Adaboost.M2-classification tree (CT), improved seagull optimisation (ISOA), a novel double-stacked autoencoder (DSAE), adaptive dynamic polar rose guided whale optimisation algorithm (AD-PRS-guided WOA), grey wolf optimisation (GWO), teaching-learning-based optimisation (TLBO), self-organising map (SOM), binary particle swarm optimisation (BPSO), improved krill herd algorithm (IKHA), artificial bee colony algorithm (ABC), improved artificial fish-swarm algorithm (IAFSA), hunter hunt algorithm optimisation, whale optimisation algorithm (WOA), gravitational search algorithm (GSA), slime mould algorithm (SMA), generative adversarial network (GAN), multiverse optimiser algorithm (MVO), improved sparrow search algorithm (ISSA), improved chimpanzee optimisation algorithm (IChOA), adaptive sparrow algorithm (ASSA), grey wolf optimisation (GWO) techniques have been shown to improve accuracy estimation and algorithm running time.

Synthetic minority oversampling technique (SMOTEBoost), GSA, and GAN are mostly used in the optimisation of parameters of the AI algorithm. In addition, GSA, GAN, and SMOTEBoost are the solutions for successfully analysing the imbalance data. SMOTE, GAN, and GSA on SVM, KNN, and radial basis function (RBF) techniques are used in parameter optimisation with high success. So, while parameter optimisation is done, there is to be successful classification rate.

Currently, there are some issues with the custom machine learning algorithm. For example, if a great difference in the recognition effect among several error types is observed, there will be a lack of machine learning. To overcome this issue, a multilevel transformer error identification system that is based on gradual grading is presented. So, parameter optimisation needs to be established. In this context, increasing datasets with strategic base oil selection, parameter optimisation techniques, optimisation performance, and high artificial intelligence method selection are very important factors for future studies. This comprehensive review aims to combine and present in a single source basic information about classical methods of power transformer fault diagnosis for DGA, historical development of the devices used, artificial intelligence-based methods, accuracy classifications of predictions.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] *IEEE Guide for the Interpretation of Gases Generated in Mineral Oil-Immersed Transformers*, IEEE Standard C57.104-2019 (Revision of IEEE Std C57.104-2008), 2019.

[2] *Guide for the Interpretation of Dissolved Gas Analysis and Gas-Free*, IEC Standard 60599, 2007.

[3] *Guide for the Sampling of Gases and of Oil-Filled Electrical Equipment and for the Analysis of Free and Dissolved Gases*, IEC Standard 60567, 2005.

[4] E. Mori *et al.*, "Latest diagnostic methods of gas-in-oil analysis for oil-filled transformer in Japan", in *Proc. of 1999 IEEE 13th International Conference on Dielectric Liquids (ICDL'99) (Cat. No.99CH36213)*, 1999, pp. 503–508. DOI: 10.1109/ICDL.1999.798982.

[5] M. Duval and L. Lamarre, "The duval pentagon - A new complementary tool for the interpretation of dissolved gas analysis in transformers", *IEEE Electrical Insulation Magazine*, vol. 30, no. 6, pp. 9–12, 2014. DOI: 10.1109/MEI.2014.6943428.

[6] S.-w. Kim, S.-j. Kim, H.-d. Seo, J.-r. Jung, H.-j. Yang, and M. Duval, "New methods of DGA diagnosis using IEC TC 10 and related databases Part 1: Application of gas-ratio combinations", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 20, no. 2, pp. 685–690, 2013. DOI: 10.1109/TDEI.2013.6508773.

[7] M. S. Ali, A. H. A. Bakar, A. Omar, A. S. A. Jaafar, and S. H. Mohamed, "Conventional methods of dissolved gas analysis using oil-immersed power transformer for fault diagnosis: A review", *Electric Power Systems Research*, vol. 216, art. 109064, 2023. DOI: 10.1016/j.epsr.2022.109064.

[8] A. Khanna and P. Bisht, "Rogers ratio test for fault diagnosis of transformer using dissolved gas analysis", *Materials Today: Proceedings*, vol. 71, part. 2, pp. 243–246, 2022. DOI: 10.1016/j.matpr.2022.08.519.

[9] R. Soni and B. Mehta, "Graphical examination of dissolved gas analysis by ratio methods and Duval triangle method to investigate

internal faults of power transformer", *Materials Today: Proceedings*, vol. 62, part. 13, pp. 7098–7103, 2022. DOI: 10.1016/j.matpr.2022.02.029.
[10] H.-C. Sun, Y.-C. Huang, and C.-M. Huang, "A review of dissolved gas analysis in power transformers", *Energy Procedia*, vol. 14, pp. 1220–1225, 2012. DOI: 10.1016/j.egypro.2011.12.1079.
[11] S. S. M. Ghoneimand and I. B. M. Taha, "A new approach of DGA interpretation technique for transformer fault diagnosis", *International Journal of Electrical Power & Energy Systems*, vol. 81, pp. 265–274, 2016. DOI: 10.1016/j.ijepes.2016.02.018.
[12] M. Duval and L. Lamarre, "The new Duval Pentagons available for DGA diagnosis in transformers filled with mineral and ester oils", in *Proc. of IEEE Electrical Insulation Conference (EIC)*, 2017, pp. 279–281. DOI: 10.1109/EIC.2017.8004683.
[13] M. Duval and J. Buchacz, "Detection of carbonization of paper in transformers using Duval Pentagon 2 and triangle 5", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 30, no. 4, pp. 1534–1539, 2023. DOI: 10.1109/TDEI.2023.3278623.
[14] T. U. Mawelela, A. F. Nnachi, A. O. Akumu, and B. T. Abe, "Fault diagnosis of power transformers using Duval triangle", in *Proc. of IEEE PES/IAS PowerAfrica*, 2020, pp. 1–5. DOI: 10.1109/PowerAfrica49420.2020.9219802.
[15] S. S. Desouky, A. E. Kalas, R. A. A. El-Aal, and A. M. M. Hassan, "Modification of Duval triangle for diagnostic transformer fault through a procedure of dissolved gases analysis", in *Proc. of 2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC)*, 2016, pp. 1–5. DOI: 10.1109/EEEIC.2016.7555796.
[16] O. Shutenko and O. Kulyk, "Comparative analysis of the defect type recognition reliability in high-voltage power transformers using different methods of DGA results interpretation", in *Proc. of 2020 IEEE Problems of Automated Electrodrive. Theory and Practice (PAEP)*, 2020, pp. 1–6. DOI: 10.1109/PAEP49887.2020.9240911.
[17] N. Pattanadech and W. Wattakapaiboon, "Application of Duval Pentagon compared with other DGA interpretation techniques: Case studies for actual transformer inspections including experience from power plants in Thailand", in *Proc. of 2019 5th International Conference on Engineering, Applied Sciences and Technology (ICEAST)*, 2019, pp. 1–4. DOI: 10.1109/ICEAST.2019.8802523.
[18] Trianto, Suwarno, Y. Li, and G.-J. Zhang, "Combining conventional and artificial intelligence DGA interpretation methods using optimized weighting factor", in *Proc. of 2016 International Seminar on Intelligent Technology and Its Applications (ISITIA)*, 2016, pp. 37–42. DOI: 10.1109/ISITIA.2016.7828630.
[19] D.-E. A. Mansour, "Development of a new graphical technique for dissolved gas analysis in power transformers based on the five combustible gases", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 22, no. 5, pp. 2507–2512, 2015. DOI: 10.1109/TDEI.2015.004999.
[20] S. A. Wani, M. U. Farooque, S. A. Khan, D. Gupta, and M. A. Khan, "Fault severity determination in transformers using dissolved gas analysis (DGA)", in *Proc. of 2015 Annual IEEE India Conference (INDICON)*, 2015, pp. 1–6. DOI: 10.1109/INDICON.2015.7443362.
[21] V. D. Bitney, V. Y. Ulyanov, and M. A. Moiseev, "The need for using various interpretation methods for power transformer DGA results", in *Proc. of 2023 5th International Youth Conference on Radio Electronics, Electrical and Power Engineering (REEPE)*, 2023, pp. 1–6. DOI: 10.1109/REEPE57272.2023.10086721.
[22] G. E. Lee, S. N. Hettiwatte, and H. A. Fonseka, "A novel visualisation technique for dissolved gas analysis datasets", in *Proc. of 2013 Australasian Universities Power Engineering Conference (AUPEC)*, 2013, pp. 1–6. DOI: 10.1109/AUPEC.2013.6725453.
[23] H. Syafruddin and H. P. Nugroho, "Dissolved Gas Analysis (DGA) for diagnosis of fault in oil-immersed power transformers: A case study", in *Proc. of 2020 4rd International Conference on Electrical, Telecommunication and Computer Engineering (ELTICOM)*, 2020, pp. 57–62. DOI: 10.1109/ELTICOM50775.2020.9230491.
[24] E. Wannapring, C. Suwanasri, and T. Suwanasri, "Dissolved Gas Analysis methods for distribution transformers", in *Proc. of 2016 13th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, 2016, pp. 1–6. DOI: 10.1109/ECTICon.2016.7561320.
[25] N. Chattranont, S. Woothipatanapan, and N. Rugthaicharoencheep, "Case study on power transformer using Dissolved Gas Analysis technique", in *Proc. of 2020 International Conference on Power, Energy and Innovations (ICPEI)*, 2020, pp. 165–168. DOI: 10.1109/ICPEI49860.2020.9431480.
[26] I. B. M. Taha, S. S. M. Ghoneim, and A. S. A. Duaywah, "Refining DGA methods of IEC Code and Rogers four ratios for transformer fault diagnosis", in *Proc. of 2016 IEEE Power and Energy Society General Meeting (PESGM)*, 2016, pp. 1–5. DOI: 10.1109/PESGM.2016.7741157.
[27] N. Chattranont, P. Wannakarn, S. Woothipatanapan, and N. Rugthaicharoencheep, "Dissolved gas analysis of 115 kV steel industry transformer using new IEEE standard", in *Proc. of 2021 18th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, 2021, pp. 603–606. DOI: 10.1109/ECTI-CON51831.2021.9454727.
[28] S. B. Wanjare and P. S. Swami, "DGA interpretation for increasing the percent of accuracy by different methods: A review", in *Proc. of 2018 International Conference on Computation of Power, Energy, Information and Communication (ICCPEIC)*, 2018, pp. 458–461. DOI: 10.1109/ICCPEIC.2018.8525179.
[29] N. A. Muhamad, B. T. Phung, T. R. Blackburn, and K. X. Lai, "Comparative study and analysis of DGA methods for transformer mineral oil", in *Proc. of 2007 IEEE Lausanne Power Tech*, 2007, pp. 45–50. DOI: 10.1109/PCT.2007.4538290.
[30] J. Haema and R. Phadungthin, "Power transformer condition evaluation by the analysis of DGA methods", in *Proc. of 2012 Asia-Pacific Power and Energy Engineering Conference*, 2012, pp. 1–4. DOI: 10.1109/APPEEC.2012.6307510.
[31] N. A. Binti Muhamad, N. Bashir, A. A. Suleiman, N. Abuja, and A. S. Alghamdi, "Asset management through effective transformer diagnostics & condition monitoring", in *Proc. of 2012 IEEE International Conference on Power and Energy (PECon)*, 2012, pp. 212–216. DOI: 10.1109/PECon.2012.6450209.
[32] P. K. Maiti, "Investigation on susceptibility of transformer oil in service to accelerated thermal stress on generation of key gases and fault diagnosis", in *Proc. of 2021 IEEE 5th International Conference on Condition Assessment Techniques in Electrical Systems (CATCON)*, 2021, pp. 321–325. DOI: 10.1109/CATCON52335.2021.9670496.
[33] Y. Zheng, C. Sun, J. Li, Q. Yang, and W. Chen, "Entropy-based Bagging for fault prediction of transformers using oil-dissolved gas data", *Energies*, vol. 4, no. 8, pp. 1138–1147, 2011. DOI: 10.3390/en4081138.
[34] E. Dornenburg and W. Strittmatter, "Monitoring oil-cooled transformers by gas analysis", *Brown Boveri Review*, vol. 61, pp. 238–247, 1974.
[35] S. Singh, D. Joshi, and M. N. Bandyopadhyay, "Software implementation of Duval Triangle technique for DGA in power transformers", *International Journal of Electrical Engineering*, vol. 4, no. 5, pp. 529–540, 2011.
[36] M. Duval, "A review of faults detectable by gas-in-oil analysis in transformers", *IEEE Electrical Insulation Magazine*, vol. 18, no. 3, pp. 8–17, 2002. DOI: 10.1109/MEI.2002.1014963.
[37] R. R. Rogers, "IEEE and IEC codes to interpret incipient faults in transformers, using gas in oil analysis", *IEEE Transactions on Electrical Insulation*, vol. EI-13, no. 5, pp. 349–354, 1978. DOI: 10.1109/TEI.1978.298141.
[38] P. K. Maiti and M. Chakraborty, "Dissolved gas analysis of thermally aged mineral oil and vegetable oil based nanofluids", in *Proc. of 2021 IEEE International Conference on the Properties and Applications of Dielectric Materials (ICPADM)*, 2021, pp. 53–56. DOI: 10.1109/ICPADM49635.2021.9493964.
[39] O. E. Gouda, S. H. El-Hoshy, and H. H. E. L. Tamaly, "Condition assessment of power transformers based on dissolved gas analysis", *IET Generation, Transmission & Distribution*, vol. 13, no. 12, pp. 2299–2310, 2019. DOI: 10.1049/iet-gtd.2018.6168.
[40] M. Chakraborty, N. Baruah, R. Sangineni, S. Nayak, and P. K. Maiti, "Dissolved Gas Analysis (DGA) of thermally aged blended transformer oil", in *Proc. of 2020 IEEE Conference on Electrical Insulation and Dielectric Phenomena (CEIDP)*, 2020, pp. 204–207. DOI: 10.1109/CEIDP49254.2020.9437452.
[41] N. L. Z. Msomi and B. A. Thango, "Development of dissolved gas analysis-based fault identification system using machine learning with Google Colab", in *Proc. of 2023 31st Southern African Universities Power Engineering Conference (SAUPEC)*, 2023, pp. 1–6. DOI: 10.1109/SAUPEC57889.2023.10057713.
[42] M. M. Ibrahim, M. M. Sayed, and E. E. Abu El-Zahab, "Diagnosis of power transformer incipient faults using Fuzzy Logic-IEC Based approach", in *Proc. of 2014 IEEE International Energy Conference (ENERGYCON)*, 2014, pp. 242–245. DOI: 10.1109/ENERGYCON.2014.6850435.
[43] K. V. Satyanarayana, C. C. Reddy, T. P. Govindan, M. Mandlik, and T. S. Ramu, "Application of artificial intelligence for the assessment of the status of power transformers", in *Conference Record of the 2008 IEEE International Symposium on Electrical Insulation*, 2008, pp. 104–107. DOI: 10.1109/ELINSL.2008.4570289.

[44] G. Dadzie, E. A. Frimpong, C. M. Allotey, and E. L. Boateng, "Transformer incipient fault detection technique based on neural network", in *Proc. of 2020 IEEE PES/IAS PowerAfrica*, 2020, pp. 1–4. DOI: 10.1109/PowerAfrica49420.2020.9219948.

[45] X. Hao and S. Cai-xin, "Artificial immune network classification algorithm for fault diagnosis of power transformer", *IEEE Transactions on Power Delivery*, vol. 22, no. 2, pp. 930–935, 2007. DOI: 10.1109/TPWRD.2007.893182.

[46] Z. Wang, Y. Liu, N.-C. Wang, T.-Y. Guo, F. T. C. Huang, and P. J. Griffin, "Artificial intelligence in power equipment fault diagnosis", in *PowerCon 2000. 2000 International Conference on Power System Technology. Proceedings (Cat. No.00EX409)*, 2000, pp. 247–252 vol. 1. DOI: 10.1109/ICPST.2000.900064.

[47] L. Wang, T. Littler, and X. Liu, "Artificial intelligence model for transformer fault diagnosis using a constructed database", in *Proc. of The 16th IET International Conference on AC and DC Power Transmission (ACDC 2020)*, 2020, pp. 1474–1479. DOI: 10.1049/icp.2020.0194.

[48] Z. Yin, Y. Zhen, C. Huo, and J. Chen, "Deep learning based transformer fault diagnosis method", in *Proc. of 2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE)*, 2021, pp. 216–219. DOI: 10.1109/ICBAIE52039.2021.9389975.

[49] D. Rediansyah, R. A. Prasojo, Suwarno, and A. Abu-Siada, "Artificial intelligence-based power transformer health index for handling data uncertainty", *IEEE Access*, vol. 9, pp. 150637–150648, 2021. DOI: 10.1109/ACCESS.2021.3125379.

[50] W. Shoupeng *et al.*, "Design and research of transformer fault diagnosis method based on data-driven", in *Proc. of 2021 International Conference on Security, Pattern Analysis, and Cybernetics (SPAC)*, 2021, pp. 228–233. DOI: 10.1109/SPAC53836.2021.9539976.

[51] Y. Qiping, X. Wude, and L. Zhida, "Development of an artificial intelligent diagnosis system for transformer fault", in *Proc. of 2005 IEEE/PES Transmission & Distribution Conference & Exposition: Asia and Pacific*, 2005, pp. 1–5. DOI: 10.1109/TDC.2005.1546920.

[52] R. Jing, H. Jia-dong, and Y. Yong-zhe, "Power transformer fault diagnosis by using the artificial immune Support Vector Machines", in *Proc. of 2009 Second International Conference on Intelligent Computation Technology and Automation*, 2009, pp. 83–86. DOI: 10.1109/ICICTA.2009.488.

[53] X. Yu and H. Zang, "Transfomer fault diagnosis based on rough sets theory and artificial neural networks", in *Proc. of 2008 International Conference on Condition Monitoring and Diagnosis*, 2008, pp. 1342–1345. DOI: 10.1109/CMD.2008.4580517.

[54] J. Li, G. Li, C. Hai, and M. Guo, "Transformer fault diagnosis based on Multi-class AdaBoost Algorithm", *IEEE Access*, vol. 10, pp. 1522–1532, 2022. DOI: 10.1109/ACCESS.2021.3135467.

[55] H. Mehdipour Picha, R. Bo, H. Chen, M. M. Rana, J. Huang, and F. Hu, "Transformer fault diagnosis using deep neural network", in *Proc. of 2019 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia)*, 2019, pp. 4241–4245. DOI: 10.1109/ISGT-Asia.2019.8881052.

[56] H. A. Illias and X. R. Chai, "Transformer insulation diagnosis using hybrid artificial intelligence-modified particle swarm optimization", in *Proc. of 2017 IEEE Conference on Energy Conversion (CENCON)*, 2017, pp. 255–258. DOI: 10.1109/CENCON.2017.8262494.

[57] L. Chao, Q. Hong, X.-H. Yang, and J.-H. Ye, "The fault diagnosis of power transformer using clustering and Radial Basis Function neural network", in *Proc. of 2009 International Conference on Machine Learning and Cybernetics*, 2009, pp. 1257–1260. DOI: 10.1109/ICMLC.2009.5212287.

[58] T. Nagpal and Y. S. Brar, "Neural network based transformer incipient fault detection", in *Proc. of 2014 International Conference on Advances in Electrical Engineering (ICAEE)*, 2014, pp. 1–5. DOI: 10.1109/ICAEE.2014.6838535.

[59] N. Poonnoy, C. Suwanasri, and T. Suwanasri, "Neural network approach to dissolved gas analysis for fault analysis in power transformers", in *Proc. of 2022 International Electrical Engineering Congress (iEECON)*, 2022, pp. 1–4. DOI: 10.1109/iEECON53204.2022.9741595.

[60] A. Salami and P. Pahlevani, "Neural network approach for fault diagnosis of transformers", in *Proc. of 2008 International Conference on Condition Monitoring and Diagnosis*, 2008, pp. 1346–1349. DOI: 10.1109/CMD.2008.4580518.

[61] L. Feng and Y. Bo, "Intelligent fault diagnosis technology of power transformer based on Artificial Intelligence", *in Proc. of 2022 IEEE 6th Information Technology and Mechatronics Engineering Conference (ITOEC)*, 2022, pp. 1968–1971. DOI: 10.1109/ITOEC53115.2022.9734331.

[62] E. Nurul Yaqin and U. Khayam, "Implementation of cognitive artificial intelligence for dissolved gas analysis interpretation in 150 kV transformer", in *Proc. of 2021 International Conference on Technology and Policy in Energy and Electric Power (ICT-PEP)*, 2021, pp. 52–57. DOI: 10.1109/ICT-PEP53949.2021.9600896.

[63] H. Malik and S. Mishra, "Feature selection using RapidMiner and classification through probabilistic neural network for fault diagnostics of power transformer", in *Proc. of 2014 Annual IEEE India Conference (INDICON)*, 2014, pp. 1–6. DOI: 10.1109/INDICON.2014.7030427.

[64] N. Van Le, "Application of artificial intelligence in diagnosis of power transformer incipient faults", in *Proc. of 2013 26th IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)*, 2013, pp. 1–4. DOI: 10.1109/CCECE.2013.6567700.

[65] F. Yang and Z. liang, "Comprehensive method detecting the status of the transformer based on the artificial intelligence", in *Proc. of 2004 International Conference on Power System Technology*, 2004, pp. 1638–1643, vol. 2. DOI: 10.1109/ICPST.2004.1460266.

[66] E. Baker, S. V. Nese, and E. Dursun, "Hybrid condition monitoring system for power transformer fault diagnosis", *Energies*, vol. 16, no. 3, p. 1151, 2023. DOI: 10.3390/en16031151.

[67] H. Malik and S. Mishra, "Extreme learning machine based fault diagnosis of power transformer using IEC TC10 and its related data", in *Proc. of 2015 Annual IEEE India Conference (INDICON)*, 2015, pp. 1–5. DOI: 10.1109/INDICON.2015.7443245.

[68] Z. Li, J. Yuan, and P. Su, "Fault diagnosis of power transformer based on heuristic reduction algorithm", in *Proc. of 2009 Asia-Pacific Power and Energy Engineering Conference*, 2009, pp. 1–4. DOI: 10.1109/APPEEC.2009.4918375.

[69] Y.-C. Huang, C.-M. Huang, H.-C. Sun, and Y.-S. Liao, "Fault diagnosis using hybrid artificial intelligent methods", in *Proc. of 2010 5th IEEE Conference on Industrial Electronics and Applications*, 2010, pp. 41–44. DOI: 10.1109/ICIEA.2010.5514760.

[70] C. Long, J. Wu, X. Xiong, Z. Chang, and R. Luo, "Fault identification method of voltage transformer based on time series hierarchical clustering", in *Proc. of 2021 11th International Conference on Power and Energy Systems (ICPES)*, 2021, pp. 447–451. DOI: 10.1109/ICPES53652.2021.9683952.

[71] K. Benhmed, A. Mooman, A. Younes, K. Shaban, and A. El-Hag, "Feature selection for effective health index diagnoses of power transformers", *IEEE Transactions on Power Delivery*, vol. 33, no. 6, pp. 3223–3226, 2018. DOI: 10.1109/TPWRD.2017.2762920.

[72] Z. Gao, X. Wang, F. Yi, W. Xu, and M. Zhu, "Transformer DGA diagnostic method based on fuzzy logic function method", in *Proc. of 2023 IEEE 11th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, 2023, pp. 1639–1642. DOI: 10.1109/ITAIC58329.2023.10408761.

[73] A. Vatsa, A. S. Hati, and A. K. Rathore, "Enhancing transformer health monitoring with AI-driven prognostic diagnosis trends: Overcoming traditional methodology's computational limitations", *IEEE Industrial Electronics Magazine*, vol. 18, no. 3, pp. 30–44, 2024. DOI: 10.1109/MIE.2023.3329277.

[74] X. Yang, M. Yue, T. Jia, and A. Sun, "Transformer fault diagnosis based on DGA information fusion", in *Proc. of 2023 4th International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE)*, 2023, pp. 241–244. DOI: 10.1109/ICBAIE59714.2023.10281246.

[75] I. M. Malik, A. Sharma, and R. T. Naayagi, "A comprehensive and practical method for transformer fault analysis with historical data trend using fuzzy logic", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 30, no. 5, pp. 2277–2284, 2023. DOI: 10.1109/TDEI.2023.3286795.

[76] A. Nanfak, S. Eke, F. Meghnefi, I. Fofana, G. M. Ngaleu, and C. H. Kom, "Hybrid DGA method for power transformer faults diagnosis based on evolutionary *k*-means clustering and dissolved gas subsets analysis", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 30, no. 5, pp. 2421–2428, 2023. DOI: 10.1109/TDEI.2023.3275119.

[77] T. Wang, J. Yang, J. Shao, P. Wu, Y. Ma, and J. Liang, "Improvement of power transformer faults diagnosis using random search with classification and regression tree", in *Proc. of 2023 5th Asia Energy and Electrical Engineering Symposium (AEEES)*, 2023, pp. 653–658. DOI: 10.1109/AEEES56888.2023.10114139.

[78] W. Lu, C. Shi, H. Fu, and Y. Xu, "Fault diagnosis method for power transformers based on Improved Golden Jackal optimization algorithm and Random Configuration Network", *IEEE Access*, vol. 11, pp. 35336–35351, 2023. DOI: 10.1109/ACCESS.2023.3265469.

[79] B. Jan, O. Rahman, S. Parveen, and S. A. Khan, "Multi-stage binary classification technique for incipient fault diagnosis of oil immersed power transformers based on ANFIS", in *Proc. of 2023 International Conference on Power, Instrumentation, Energy and Control (PIECON)*, 2023, pp. 1–6. DOI: 10.1109/PIECON56912.2023.10085900.

[80] J. F. Vidal and A. R. G. Castro, "Diagnosing faults in power transformers with variational autoencoder, genetic programming, and neural network", *IEEE Access*, vol. 11, pp. 30529–30545, 2023. DOI: 10.1109/ACCESS.2023.3258544.

[81] L. Wang, T. Littler, and X. Liu, "Dynamic incipient fault forecasting for power transformers using an LSTM model", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 30, no. 3, pp. 1353–1361, 2023. DOI: 10.1109/TDEI.2023.3253463.

[82] K. N. V. P. S. Rajesh, U. M. Rao, I. Fofana, P. Rozga, and A. Paramane, "Influence of data balancing on transformer DGA fault classification with machine learning algorithms", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 30, no. 1, pp. 385–392, 2023. DOI: 10.1109/TDEI.2022.3230377.

[83] S. S. Baiju and A. S, "Root cause analysis in power transformer failure with improved intelligent methods", in *Proc. of 2022 IEEE International Power and Renewable Energy Conference (IPRECON)*, 2022, pp. 1–6. DOI: 10.1109/IPRECON55716.2022.10059538.

[84] M. Badawi, S. A. Ibrahim, A. El-Faraskoury, D.-E. A. Mansour, and S. A. Ward, "A novel DGA oil interpretation approach based on combined techniques", in *Proc. of 2022 23rd International Middle East Power Systems Conference (MEPCON)*, 2022, pp. 01–08. DOI: 10.1109/MEPCON55441.2022.10021795.

[85] C. Gao, E. Gao, Z. Yang, Y. Feng, B. Song, and Q. Li, "Transformer fault diagnosis method based on membership degree of dissolved gas", in *Proc. of 2022 IEEE International Conference on High Voltage Engineering and Applications (ICHVE)*, 2022, pp. 01–04. DOI: 10.1109/ICHVE53725.2022.9961664.

[86] X. Wang *et al.*, "Power transformer defect prediction method based on SMOTE and random forest algorithm", in *Proc. of 2022 IEEE International Conference on High Voltage Engineering and Applications (ICHVE)*, 2022, pp. 1–4. DOI: 10.1109/ICHVE53725.2022.9961386.

[87] J. Yan, J. Zhang, Z. Duan, Y. Wang, S. Zhao, and L. Wang, "Research on transformer fault detection method based on chaos algorithm", in *Proc. of 2022 4th International Conference on Power and Energy Technology (ICPET)*, 2022, pp. 438–444. DOI: 10.1109/ICPET55165.2022.9918268.

[88] F. Ru, L. Zhang, X. Yang, H. Zou, Y. Lu, and X. Xu, "Transformer fault diagnosis based on dissolved gas analysis in oil and ensemble learning", in *Proc. of 2022 IEEE 5th International Electrical and Energy Conference (CIEEC)*, 2022, pp. 3174–3178. DOI: 10.1109/CIEEC54735.2022.9846076.

[89] M. Badawi *et al.*, "Reliable estimation for health index of transformer oil based on novel combined predictive maintenance techniques", *IEEE Access*, vol. 10, pp. 25954–25972, 2022. DOI: 10.1109/ACCESS.2022.3156102.

[90] A. G. C. Menezes, M. M. Araujo, O. M. Almeida, F. R. Barbosa, and A. P. S. Braga, "Induction of decision trees to diagnose incipient faults in power transformers", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 29, no. 1, pp. 279–286, 2022. DOI: 10.1109/TDEI.2022.3148453.

[91] Y. Wu, X. Sun, Y. Zhang, X. Zhong, and L. Cheng, "A power transformer fault diagnosis method-based hybrid improved Seagull Optimization Algorithm and Support Vector Machine", *IEEE Access*, vol. 10, pp. 17268–17286, 2022. DOI: 10.1109/ACCESS.2021.3127164.

[92] D. Yang, J. Qin, Y. Pang, and T. Huang, "A novel double-stacked autoencoder for power transformers DGA signals with an imbalanced data structure", *IEEE Transactions on Industrial Electronics*, vol. 69, no. 2, pp. 1977–1987, 2022. DOI: 10.1109/TIE.2021.3059543.

[93] W. Cui, M. Chu, C. Ding, Y. Wang, M. Wang, and L. Liu, "Research on the fault diagnosis method of oil-immersed transformers based on the improved DBSCAN algorithm", in *Proc. of 2021 China Automation Congress (CAC)*, 2021, pp. 5171–5176. DOI: 10.1109/CAC53003.2021.9728677.

[94] T. H. Dwiputranto, N. Akhmad Setiawan, and T. B. Adji, "DGA-based early transformer fault detection using GA-optimized ANN", in *Proc. of 2021 International Conference on Technology and Policy in Energy and Electric Power (ICT-PEP)*, 2021, pp. 342–347. DOI: 10.1109/ICT-PEP53949.2021.9601111.

[95] L. Wang, T. Littler, and X. Liu, "Gaussian process multi-class classification for transformer fault diagnosis using dissolved gas analysis", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 28, no. 5, pp. 1703–1712, 2021. DOI: 10.1109/TDEI.2021.009470.

[96] H. A. Illias, C. K. Choon, W. Z. Liang, H. Mokhlis, A. M. Ariffin, and M. F. M. Yousof, "Fault identification in power transformers using Dissolve Gas Analysis and Support Vector Machine", in *Proc. of 2021 IEEE International Conference on the Properties and Applications of Dielectric Materials (ICPADM)*, 2021, pp. 33–36. DOI: 10.1109/ICPADM49635.2021.9493970.

[97] O. Kherif, Y. Benmahamed, M. Teguar, A. Boubakeur, and S. S. M. Ghoneim, "Accuracy improvement of power transformer faults diagnostic using KNN classifier with decision tree principle", *IEEE Access*, vol. 9, pp. 81693–81701, 2021. DOI: 10.1109/ACCESS.2021.3086135.

[98] S. S. M. Ghoneim, T. A. Farrag, A. A. Rashed, El.-S. M. El-Kenawy, and A. Ibrahim, "Adaptive dynamic meta-heuristics for feature selection and classification in diagnostic accuracy of transformer faults", *IEEE Access*, vol. 9, pp. 78324–78340, 2021. DOI: 10.1109/ACCESS.2021.3083593.

[99] S. S. M. Ghoneim, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "Enhancing diagnostic accuracy of transformer faults using teaching-learning-based optimization", *IEEE Access*, vol. 9, pp. 30817–30832, 2021. DOI: 10.1109/ACCESS.2021.3060288.

[100] A. Mekkayil, G. Pillai, and M. Malcolm, "A spreadsheet based dissolved gas analysis diagnostic tool for oil-filled transformers", in *Proc. of 2020 55th International Universities Power Engineering Conference (UPEC)*, 2020, pp. 1–6. DOI: 10.1109/UPEC49904.2020.9209831.

[101] M. Meira, I. Carlucho, R. Álvarez, L. Catalano, and G. Acosta, "DGA: A novel strategy for key gases identification in power transformers", in *Proc. of 2020 IEEE Electrical Insulation Conference (EIC)*, 2020, pp. 290–293. DOI: 10.1109/EIC47619.2020.9158662.

[102] S. Misbahulmunir, V. K. Ramachandaramurthy, and Y. H. MD. Thayoob, "Improved Self-Organizing Map Clustering of power transformer Dissolved Gas Analysis using inputs pre-processing", *IEEE Access*, vol. 8, pp. 71798–71811, 2020. DOI: 10.1109/ACCESS.2020.2986726.

[103] N. Ardi, N. A. Setiawan, and T. B. Adji, "Analytical incremental learning for power transformer incipient fault diagnosis based on Dissolved Gas Analysis", in *Proc. of 2019 5th International Conference on Science and Technology (ICST)*, 2019, pp. 1–4. DOI: 10.1109/ICST47872.2019.9166441.

[104] A. R. S. Enriquez, S. L. Lima, and O. R. Saavedra, "Optimal selection of input variables by BPSO for diagnosis of incipient failures in power transformers (by DGA)", in *Proc. of 2019 20th International Conference on Intelligent System Application to Power Systems (ISAP)*, 2019, pp. 1–6. DOI: 10.1109/ISAP48318.2019.9065939.

[105] H. Duan, H. Xie, and Y. Lu, "Transformer on-line monitoring and fault diagnosis system based on DRNN and PAS", in *Proc. of 2019 IEEE 9th International Conference on Electronics Information and Emergency Communication (ICEIEC)*, 2019, pp. 1–4. DOI: 10.1109/ICEIEC.2019.8784584.

[106] Y. Zhang *et al.*, "A fault diagnosis model of power transformers based on dissolved gas analysis features selection and improved krill herd algorithm optimized support vector machine", *IEEE Access*, vol. 7, pp. 102803–102811, 2019. DOI: 10.1109/ACCESS.2019.2927018.

[107] E. Li, L. Wang, and B. Song, "Fault diagnosis of power transformers with membership degree", *IEEE Access*, vol. 7, pp. 28791–28798, 2019. DOI: 10.1109/ACCESS.2019.2902299.

[108] J. Faiz and M. Soleimani, "Assessment of computational intelligence and conventional dissolved gas analysis methods for transformer fault diagnosis", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 25, no. 5, pp. 1798–1806, 2018. DOI: 10.1109/TDEI.2018.007191.

[109] Y. Zhang, H. Peng, J. Fang, L. Zhao, X. Li, and C. Liao, "Transformer fault diagnosis based on new features selection and artificial bee colony optimization SVM", in *Proc. of 2018 International Conference on Power System Technology (POWERCON)*, 2018, pp. 3607–3613. DOI: 10.1109/POWERCON.2018.8602231.

[110] K. Chatterjee, V. K. Jadoun, and R. K. Jarial, "Emerging trends for determining incipient faults by dissolved gas analysis", in *Proc. of 2017 3rd International Conference on Condition Assessment Techniques in Electrical Systems (CATCON)*, 2017, pp. 63–68. DOI: 10.1109/CATCON.2017.8280185.

[111] A. Lakehal, F. Tachi, and H. Cheghib, "A new contribution for fault prediction of electrical power transformers", in *Proc. of 2017 6th International Conference on Systems and Control (ICSC)*, 2017, pp. 372–376. DOI: 10.1109/ICoSC.2017.7958645.

[112] M. S. Taneja, K. Pandey, and S. Sehrawat, "A review on prognosis and diagnosis of transformer oil quality using intelligent techniques based on dissolved gas analysis", in *Proc. of 2016 7th India International Conference on Power Electronics (IICPE)*, 2016, pp. 1–6. DOI: 10.1109/IICPE.2016.8079419.

[113] C. Q. Su, "A new fuzzy logic method for transformer incipient fault diagnosis", in *Proc. of 2016 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, 2016, pp. 324–327. DOI: 10.1109/FUZZ-IEEE.2016.7737704.

[114] H. Malik and S. Mishra, "Application of gene expression programming (GEP) in power transformers fault diagnosis using DGA", *IEEE*

Transactions on Industry Applications, vol. 52, no. 6, pp. 4556–4565, 2016. DOI: 10.1109/TIA.2016.2598677.

[115] J. Golarz, "Understanding Dissolved Gas Analysis (DGA) techniques and interpretations", in *Proc. of 2016 IEEE/PES Transmission and Distribution Conference and Exposition (T&D)*, 2016, pp. 1–5. DOI: 10.1109/TDC.2016.7519852.

[116] I. B. M. Taha, S. S. M. Ghoneim, and H. G. Zaini, "Improvement of Rogers four ratios and IEC Code methods for transformer fault diagnosis based on Dissolved Gas Analysis", in *Proc. of 2015 North American Power Symposium (NAPS)*, 2015, pp. 1–5. DOI: 10.1109/NAPS.2015.7335098.

[117] A. Lakehal, Z. Ghemari, and S. Saad, "Transformer fault diagnosis using dissolved gas analysis technology and Bayesian networks", in *Proc. of 2015 4th International Conference on Systems and Control (ICSC)*, 2015, pp. 194–198. DOI: 10.1109/ICoSC.2015.7152759.

[118] S. Singh and D. Joshi, "Computer applications in fault diagnosis of power transformers - A review", in *Proc. of 2015 2nd International Conference on Computing for Sustainable Global Development (INDIACom)*, 2015, pp. 1216–1223.

[119] W. Li, H. Huang, C. Wang, and H. Tang, "Synthetic fault diagnosis method of power transformer based on rough set theory and improved artificial immune network classification algorithm", in *Proc. of 2008 Fourth International Conference on Natural Computation*, 2008, pp. 676–681. DOI: 10.1109/ICNC.2008.214.

[120] H. Malik and S. Mishra, "Fault identification of power transformers using Proximal Support Vector Machine (PSVM)", in *Proc. of 2014 IEEE 6th India International Conference on Power Electronics (IICPE)*, 2014, pp. 1–5. DOI: 10.1109/IICPE.2014.7115842.

[121] D. R. Malabanan and A. C. Nerves, "Power transformer condition assessment using an immune neural network approach to Dissolved Gas Analysis", in *Proc of TENCON 2014 - 2014 IEEE Region 10 Conference*, 2014, pp. 1–6. DOI: 10.1109/TENCON.2014.7022327.

[122] Z. Xiao-Li, W. Shen-Qiang, C. Yan-Zhao, and W. Lei-Yuan, "Transformer fault diagnosis based on improved fuzzy ISODATA algorithm", in *Proc. of 2014 International Conference on Power System Technology*, 2014, pp. 1279–1286. DOI: 10.1109/POWERCON.2014.6993582.

[123] Y. Cui, H. Ma, and T. Saha, "Improvement of power transformer insulation diagnosis using oil characteristics data preprocessed by SMOTEBoost technique", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 21, no. 5, pp. 2363–2373, 2014. DOI: 10.1109/TDEI.2014.004547.

[124] A. K. Mehta, R. N. Sharma, S. Chauhan, and S. Saho, "Transformer diagnostics under dissolved gas analysis using Support Vector Machine", in *Proc. of 2013 International Conference on Power, Energy and Control (ICPEC)*, 2013, pp. 181–186. DOI: 10.1109/ICPEC.2013.6527647.

[125] Y.-C. Huang and H.-C. Sun, "Dissolved gas analysis of mineral oil for power transformer fault diagnosis using fuzzy logic", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 20, no. 3, pp. 974–981, 2013. DOI: 10.1109/TDEI.2013.6518967.

[126] H. Ma, C. Ekanayake, and T. K. Saha, "Power transformer fault diagnosis under measurement originated uncertainties", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 19, no. 6, pp. 1982–1990, 2012. DOI: 10.1109/TDEI.2012.6396956.

[127] C. Xiaoqing, L. Juemin, H. Yingwei, and F. Bo, "Transformer fault diagnosis based on IAFSA and rough set", in *Proc. of 26th International Conference on Electrical Contacts (ICEC 2012)*, 2012, pp. 296–300. DOI: 10.1049/cp.2012.0664.

[128] A. N. Souza, C. C. O. Ramos, D. S. Gastaldello, R. Y. M. Nakamura, and J. P. Papa, "Fast fault diagnosis in power transformers using Optimum-Path Forest", in *Proc. of 2012 IEEE 16th International Conference on Intelligent Engineering Systems (INES)*, 2012, pp. 209–212. DOI: 10.1109/INES.2012.6249832.

[129] L. Zheng, W. Liu, and L. Lu, "Application of BP network based on free-weighting on transformer fault diagnosis", in *Proc. of 2011 6th IEEE Joint International Information Technology and Artificial Intelligence Conference*, 2011, pp. 229–232. DOI: 10.1109/ITAIC.2011.6030317.

[130] I. S. Msiza, M. Szewczyk, A. Halinka, J.-H. C. Pretorius, P. Sowa, and T. Marwala, "Neural networks on transformer fault detection evaluating the relevance of the input space parameters", in *Proc. of 2011 IEEE/PES Power Systems Conference and Exposition*, 2011, pp. 1–6. DOI: 10.1109/PSCE.2011.5772567.

[131] L. Song, L. Xiu-ying, and W. Wen-xu, "Fault diagnosis of transformer based on probabilistic neural network", in *Proc. of 2011 Fourth International Conference on Intelligent Computation Technology and Automation*, 2011, pp. 128–131. DOI: 10.1109/ICICTA.2011.39.

[132] Z. Zhang, Y.-L. Zhu, Z.-L. Wu, and K. Han, "Diagnosis of transformer dissolved gas analysis based on multi-class SVM", in *Proc. of 2009 International Conference on Artificial Intelligence and Computational Intelligence*, 2009, pp. 463–466. DOI: 10.1109/AICI.2009.108.

[133] Z. Xue, X. Sun, and Y. Liang, "Application of data mining technology based on FRS and SVM for fault identification of power transformer", in *Proc. of 2009 International Conference on Artificial Intelligence and Computational Intelligence*, 2009, pp. 452–455. DOI: 10.1109/AICI.2009.196.

[134] X. Zhao and Y. Yun, "A fault diagnosis method combined fuzzy logic with CMAC neural network for power transformers", in *Proc. of 2009 Chinese Conference on Pattern Recognition*, 2009, pp. 1–5. DOI: 10.1109/CCPR.2009.5343998.

[135] J. Nejedly and L. Potacek, "Fault diagnosis of 110 kV instrument transformers through DGA and the application of artificial intelligence", in *Proc. of CIRED 2009 - 20th International Conference and Exhibition on Electricity Distribution - Part 1*, 2009, pp. 1–3. DOI: 10.1049/cp.2009.0508.

[136] A. Singh and P. Verma, "A review of intelligent diagnostic methods for condition assessment of insulation system in power transformers", in *Proc. of 2008 International Conference on Condition Monitoring and Diagnosis*, 2008, pp. 1354–1357. DOI: 10.1109/CMD.2008.4580520.

[137] X. Hao, C. Tao, L. Rui-jing, L. Jian, and S. Cai-xin, "Fault diagnosis of power transformer using kernel-based possibilistic clustering", in *Proc. of 2006 International Conference on Power System Technology*, 2006, pp. 1–5. DOI: 10.1109/ICPST.2006.321491.

[138] J.-h. Sun, S.-b. Han, S.-h. Yi, D.-s. Kang, and K.-h. Kim, "Development of oil immersed transformer management technologies by using dissolved gas analysis", in *Proc. of 2006 IEEE 8th International Conference on Properties & applications of Dielectric Materials*, 2006, pp. 683–686. DOI: 10.1109/ICPADM.2006.284269.

[139] D. R. Morais and J. G. Rolim, "A hybrid tool for detection of incipient faults in transformers based on the dissolved gas analysis of insulating oil", *IEEE Transactions on Power Delivery*, vol. 21, no. 2, pp. 673–680, 2006. DOI: 10.1109/TPWRD.2005.864044.

[140] Z. Zhong, S. Tang, G. Peng, and Y. Zhang, "A novel quantitative spectral analysis method based on parallel BP neural network for dissolved gas in transformer oil", in *Proc. of 2016 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, 2016, pp. 1979–1983. DOI: 10.1109/APPEEC.2016.7779840.

[141] X. Ding and H. Cai, "On-line transformer winding's fault monitoring and condition assessment", in *Proc. of 2001 International Symposium on Electrical Insulating Materials (ISEIM 2001). 2001 Asian Conference on Electrical Insulating Diagnosis (ACEID 2001). 33rd Symposium on Electrical and Ele*, 2001, pp. 801–804. DOI: 10.1109/ISEIM.2001.973799.

[142] Z. Wang, Y. Liu, and P. J. Griffin, "Neural net and expert system diagnose transformer faults", *IEEE Computer Applications in Power*, vol. 13, no. 1, pp. 50–55, 2000. DOI: 10.1109/67.814667.

[143] J. Lin, G. Sheng, Y. Gao, Y. Yan, and X. Jiang, "Fault diagnosis of transformer based on KPCA and Elman neural network", in *Proc. of 2018 IEEE International Conference on Industrial Technology (ICIT)*, 2018, pp. 1232–1235. DOI: 10.1109/ICIT.2018.8352354.

[144] S. Das, A. Paramane, S. Chatterjee, and U. M. Rao, "Accurate identification of transformer faults from dissolved gas data using recursive feature elimination method", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 30, no. 1, pp. 466–473, 2023. DOI: 10.1109/TDEI.2022.3215936.

[145] I. B. M. Taha, A. Hoballah, and S. S. M. Ghoneim, "Optimal ratio limits of Rogers' four-ratios and IEC 60599 code methods using particle swarm optimization fuzzy-logic approach", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 27, no. 1, pp. 222–230, 2020. DOI: 10.1109/TDEI.2019.008395.

[146] S. S. M. Ghoneim, I. B. M. Taha, and N. I. Elkalashy, "Integrated ANN-based proactive fault diagnostic scheme for power transformers using dissolved gas analysis", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 23, no. 3, pp. 1838–1845, 2016. DOI: 10.1109/TDEI.2016.005301.

[147] U. M. Rao, I. Fofana, A. Betie, M. L. Senoussaoui, M. Brahami, and E. Briosso, "Condition monitoring of in-service oil-filled transformers: Case studies and experience", *IEEE Electrical Insulation Magazine*, vol. 35, no. 6, pp. 33–42, 2019. DOI: 10.1109/MEI.2019.8878258.

[148] U. M. Rao, I. Fofana, K. N. V. P. S. Rajesh, and P. Picher, "Identification and application of machine learning algorithms for transformer dissolved gas analysis", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 28, no. 5, pp. 1828–1835, 2021. DOI: 10.1109/TDEI.2021.009770.

[149] A. Akbari, A. Setayeshmehr, H. Borsi, E. Gockenbach, and I. Fofana, "Intelligent agent-based system using dissolved gas analysis to detect incipient faults in power transformers", *IEEE Electrical Insulation Magazine*, vol. 26, no. 6, pp. 27–40, 2010. DOI: 10.1109/MEI.2010.5599977.

[150] L. Jin, D. Kim, K. Y. Chan, and A. Abu-Siada, "Deep machine learning-based asset management approach for oil-immersed power transformers using dissolved gas analysis", *IEEE Access*, vol. 12, pp. 27794–27809, 2024. DOI: 10.1109/ACCESS.2024.3366905.

[151] X. Yang, Y. Yin, T. Jia, and M. Yue, "Transformer fault diagnosis method based on hunter hunt algorithm optimization", in *Proc. of 2023 10th International Forum on Electrical Engineering and Automation (IFEEA)*, 2023, pp. 1045–1048. DOI: 10.1109/IFEEA60725.2023.10429452.

[152] G. Venkateshwari, R. Ananthi, S. S. Abirami, C. M. Lakshmi Rama, T. Sangeetha, and B. Vigneshwaran, "Semi-supervised learning based power transformer health monitoring index using deep learning", in *Proc. of 2023 7th International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, 2023, pp. 530–534. DOI: 10.1109/ICECA58529.2023.10395439.

[153] M. Liu *et al.*, "Selection of attribute indicators in transformer fault diagnosis based on fuzzy clustering", in *Proc. of 2023 3rd International Conference on Intelligent Power and Systems (ICIPS)*, 2023, pp. 224–228. DOI: 10.1109/ICIPS59254.2023.10405192.

[154] Z. Jing, H. Zhang, and P. Yang, "Analysis method of dissolved gas in power transformer oil based on fuzzy reinforcement learning", in *Proc. of 2023 5th International Conference on Power and Energy Technology (ICPET)*, 2023, pp. 148–152. DOI: 10.1109/ICPET59380.2023.10367721.

[155] N. Hirkaney and S. Lall, "Comparison of fault identification methods for analyzing transformer dissolved gas", in *Proc. of 2023 3rd International Conference on Energy, Power and Electrical Engineering (EPEE)*, 2023, pp. 902–907. DOI: 10.1109/EPEE59859.2023.10351906.

[156] X. Sun, "Research on machine learning based fault diagnosis methods for power transformers", in *Proc. of 2023 IEEE 5th International Conference on Civil Aviation Safety and Information Technology (ICCASIT)*, 2023, pp. 1309–1315. DOI: 10.1109/ICCASIT58768.2023.10351584.

[157] R. A. Prasojo, H. F. W. Azizi, I. Kurniawan, Suwarno, H. Sutikno, and I. Ridzki, "Naïve Bayes model for combining results from multi-methods fault identification of power transformer", in *Proc. of 2023 4th International Conference on High Voltage Engineering and Power Systems (ICHVEPS)*, 2023, pp. 199–203. DOI: 10.1109/ICHVEPS58902.2023.10257469.

[158] Z. Fan, K. Bai, and X. Zheng, "Hybrid GA and improved CNN algorithm for power plant transformer condition monitoring model", *IEEE Access*, vol. 12, pp. 60255–60263, 2024. DOI: 10.1109/ACCESS.2023.3316251.

[159] Z. Li, Y. Qian, Q. Wang, and Y. Zhao, "Research on the transformer fault diagnosis method based on LSTM artificial neural network and DGA", in *Proc. of 2022 International Conference on Intelligent Computing and Machine Learning (2ICML)*, 2023, pp. 42–46. DOI: 10.1109/2ICML58251.2022.00018.

[160] S. D. Patil, A. J. Patil, M. Dharme, and R. K. Jarial, "DGA based ensemble learning approach for power transformer fault diagnosis", in *Proc. of 2023 International Conference in Advances in Power, Signal, and Information Technology (APSIT)*, 2023, pp. 722–727. DOI: 10.1109/APSIT58554.2023.10201755.

[161] W. Liao, Y. Zhang, D. Cao, T. Ishizaki, Z. Yang, and D. Yang, "Explainable fault diagnosis of oil-immersed transformers: A glass-box model", *IEEE Transactions on Instrumentation and Measurement*, vol. 73, art no. 2506204, pp. 1–4, 2024. DOI: 10.1109/TIM.2024.3350131.

[162] W. Zhang *et al.*, "Residual lifetime evaluation of power transformers based on data fusion and Wiener model", *IEEE Transactions on Power Delivery*, vol. 38, no. 6, pp. 4189–4201, 2023. DOI: 10.1109/TPWRD.2023.3305732.

[163] M. N. Ali, M. Amer, and M. Elsisi, "Reliable IoT paradigm with ensemble machine learning for faults diagnosis of power transformers considering adversarial attacks", *IEEE Transactions on Instrumentation and Measurement*, vol. 72, art no. 3525413, pp. 1–13, 2023. DOI: 10.1109/TIM.2023.3300444.

[164] H. C. Chen, Y. Zhang, and M. Chen, "Transformer dissolved gas analysis for highly-imbalanced dataset using multiclass sequential ensembled ELM", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 30, no. 5, pp. 2353–2361, 2023. DOI: 10.1109/TDEI.2023.3280436.

[165] S. Saroja, S. Haseena, and R. Madavan, "Dissolved gas analysis of transformer: An approach based on ML and MCDM", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 30, no. 5, pp. 2429–2438, 2023. DOI: 10.1109/TDEI.2023.3271609.

[166] D. Luo *et al.*, "Prediction for dissolved gas in power transformer oil based on TCN and GCN", *IEEE Transactions on Industry Applications*, vol. 58, no. 6, pp. 7818–7826, 2022. DOI: 10.1109/TIA.2022.3197565.

[167] N. Haque, A. Jamshed, K. Chatterjee, and S. Chatterjee, "Accurate sensing of power transformer faults from dissolved gas data using random forest classifier aided by data clustering method", *IEEE Sensors Journal*, vol. 22, no. 6, pp. 5902–5910, 2022. DOI: 10.1109/JSEN.2022.3149409.

[168] Y. Zhang *et al.*, "Early warning of incipient faults for power transformer based on DGA using a two-stage feature extraction technique", *IEEE Transactions on Power Delivery*, vol. 37, no. 3, pp. 2040–2049, 2022. DOI: 10.1109/TPWRD.2021.3103455.

[169] J. Li, C. Hai, Z. Feng, and G. Li, "A transformer fault diagnosis method based on parameters optimization of hybrid kernel extreme learning machine", *IEEE Access*, vol. 9, pp. 126891–126902, 2021. DOI: 10.1109/ACCESS.2021.3112478.

[170] L. Yong, Z. Lei, X. Ziqiang, X. Yusong, and J. Xuebiao, "Prediction model of dissolved gas in transformer oil based on EMD and BiGRU", in *Proc. of 2023 5th Asia Energy and Electrical Engineering Symposium (AEEES)*, 2023, pp. 1460–1464. DOI: 10.1109/AEEES56888.2023.10114071.

[171] Z. Xing, Y. He, X. Wang, K. Shao, and J. Duan, "VMD-IARIMA-based time-series forecasting model and its application in dissolved gas analysis", *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 30, no. 2, pp. 802–811, 2023. DOI: 10.1109/TDEI.2022.3228222.

[172] J. E., Y. Zhang, W. He, W. Zhang, Y. Cao, and G. Lv, "A new method for oil-immersed transformers fault diagnosis based on evidential reasoning rule with optimized probabilistic distributed", *IEEE Access*, vol. 12, pp. 34289–34305, 2024. DOI: 10.1109/ACCESS.2024.3370866.

[173] S. Cvijic, N. Gupta, and S. Lux, "Need for AI in transformer diagnostics and prognostics", in *Proc. of 2023 Annual Reliability and Maintainability Symposium (RAMS)*, 2023, pp. 1–7. DOI: 10.1109/RAMS51473.2023.10088199.

[174] R. A. Raj, S. D, S. K. Venkatachary, and L. J. B. Andrews, "Classification and prediction of incipient faults in transformer oil by supervised machine learning using decision tree", in *Proc. of 2023 3rd International conference on Artificial Intelligence and Signal Processing (AISP)*, 2023, pp. 1–6. DOI: 10.1109/AISP57993.2023.10134566.

[175] A. Zambrano, S. Grau, U. Stecchi, D. Stratogiannis, E. Daridou, and H. Keko, "Predictive maintenance of power transformers based on a data-driven application", in *Proc. of 2023 3rd International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*, 2023, pp. 1–6. DOI: 10.1109/ICECCME57830.2023.10252955.

[176] M. Demirci, M. Saka, H. Gozde, M. Dursun, and M. C. Taplamacioglu, "Dempster Shafer Evidence Theory application for fault diagnosis of power transformers", in *Proc. of 2022 9th International Conference on Electrical and Electronics Engineering (ICEEE)*, 2022, pp. 40–44. DOI: 10.1109/ICEEE55327.2022.9772608.

[177] M. Demirci, H. Gozde, and M. C. Taplamacioglu, "Fault diagnosis of power transformers with machine learning methods using traditional methods data", *International Journal on "Technical and Physical Problems of Engineering" (IJTPE)*, vol. 13, no. 4, pp. 225–230, 2021.

[178] S. Kim, J. Park, W. Kim, S.-H. Jo, and B. D. Youn, "Learning from even a weak teacher: Bridging rule-based Duval method and a deep neural network for power transformer fault diagnosis", *International Journal of Electrical Power & Energy Systems*, vol. 136, art. 107619, 2022. DOI: 10.1016/j.ijepes.2021.107619.

[179] J. I. Aizpurua, V. M. Catterson, B. G. Stewart, S. D. J. McArthur, B. Lambert, and J. G. Cross, "Uncertainty-aware fusion of probabilistic classifiers for improved transformer diagnostics", *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, no. 1, pp. 621–633, 2021. DOI: 10.1109/TSMC.2018.2880930.

[180] D. Bhalla, R. K. Bansal, and H. O. Gupta, "Integrating AI based DGA fault diagnosis using Dempster–Shafer Theory", *International Journal of Electrical Power & Energy Systems*, vol. 48, pp. 31–38, 2013. DOI: 10.1016/j.ijepes.2012.11.018.

[181] H. Zhou and S. Bin, "Research on application of multivariate cumulative chart in transformer fault warning", in *Proc. of 2022 4th International Conference on Electrical Engineering and Control Technologies (CEECT)*, 2022, pp. 369–373. DOI: 10.1109/CEECT55960.2022.10030733.

[182] H. A. Illias, K. C. Chan, and H. Mokhlis, "Hybrid feature selection–artificial intelligence–gravitational search algorithm technique for automated transformer fault determination based on dissolved gas analysis", *IET Generation, Transmission & Distribution*, vol. 14, no. 8, pp. 1575–1582, 2020. DOI: 10.1049/iet-gtd.2019.1189.

[183] S.-w. Fei and X.-b. Zhang, "Fault diagnosis of power transformer based on support vector machine with genetic algorithm", *Expert Systems with Applications*, vol. 36, no. 8, pp. 11352–11357, 2009. DOI: 10.1016/j.eswa.2009.03.022.

[184] H. Zheng, Y. Zhang, J. Liu, H. Wei, J. Zhao, and R. Liao, “A novel model based on wavelet LS-SVM integrated improved PSO algorithm for forecasting of dissolved gas contents in power transformers”, *Electric Power Systems Research*, vol. 155, pp. 196–205, 2018. DOI: 10.1016/j.epsr.2017.10.010.

[185] Z. Li *et al.*, “Online implementation of SVM based fault diagnosis strategy for PEMFC systems”, *Applied Energy*, vol. 164, pp. 284–293, 2016. DOI: 10.1016/j.apenergy.2015.11.060.

[186] C. Xu, X. Li, Z. Wang, B. Zhao, and J. Xie, “Improved BLS based transformer fault diagnosis considering imbalanced samples”, *Energy Reports*, vol. 8, no. 5, pp. 1446–1453, 2022. DOI: 10.1016/j.egyr.2022.02.223.

[187] H. Zheng and R. Shioya, “A comparison between artificial intelligence method and standard diagnosis methods for power transformer dissolved gas analysis using two public databases”, *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 15, no. 9, pp. 1305–1311, 2020. DOI: 10.1002/Tee.23197.

[188] M. El A. Senoussaoui, M. Brahami, and I. Fofana, “Combining and comparing various machine-learning algorithms to improve dissolved gas analysis interpretation”, *IET Generation, Transmission & Distribution*, vol. 12, no. 15, pp. 3673–3679, 2018. DOI: 10.1049/iet-gtd.2018.0059.

[189] C. Wei, W. Tang, and Q. Wu, “Dissolved gas analysis method based on novel feature prioritisation and support vector machine”, *IET Electric Power Applications*, vol. 8, no. 8, pp. 320–328, 2014. DOI: 10.1049/iet-epa.2014.0085.

[190] Y.-C. Huang, C.-M. Huang, and H.-C. Sun, “Data mining for oil-insulated power transformers: an advanced literature survey”, *WIREs Data Mining and Knowledge Discovery*, vol. 2, no. 2, pp. 138–148, 2012. DOI: 10.1002/widm.1043.

[191] Md M. Islam, G. Lee, and S. N. Hettiwatte, “Application of Parzen Window estimation for incipient fault diagnosis in power transformers”, *High Voltage*, vol. 3, no. 4, pp. 303–309, 2018. DOI: 10.1049/hve.2018.5061.

[192] L. Wang, T. Littler, and X. Liu, “Hybrid AI model for power transformer assessment using imbalanced DGA datasets”, *IET Renewable Power Generation*, vol. 17, no. 8, pp. 1912–1922, 2023. DOI: 10.1049/rpg2.12733.

[193] H. Zhang, J. Sun, K. Hou, Q. Li, and H. Liu, “Improved information entropy weighted vague support vector machine method for transformer fault diagnosis”, *High Voltage*, vol. 7, no. 3, pp. 510–522, 2022. DOI: 10.1049/hve2.12095.

[194] X. Wang and T. Han, “Transformer fault diagnosis based on stacking ensemble learning”, *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 15, pp. 1734–1739, 2020. DOI: 10.1002/tee.23247.

[195] C.-H. Lin, J.-L. Chen, and P.-Z. Huang, “Dissolved gases forecast to enhance oil-immersed transformer fault diagnosis with grey prediction–clustering analysis”, *Expert Systems*, vol. 28, no. 2, pp. 123–137, 2011. DOI: 10.1111/j.1468-0394.2010.00542.x.

[196] J. Aghaei, A. Gholami, H. A. Shayanfar, and A. Dezhamkhooy, “Dissolved gas analysis of transformers using fuzzy logic approach”, *European Transactions on Electrical Power*, vol. 20, pp. 630–638, 2010. DOI: 10.1002/etep.343.

[197] C.-H. Liu, T.-B. Lin, L. Yao, and S.-Y. Wang, “Integrated power transformer diagnosis using hybrid fuzzy dissolved gas analysis”, *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 10, no. 6, pp. 689–698, 2015. DOI: 10.1002/tee.22148.

[198] S. S. M. Ghoneim, “Intelligent prediction of transformer faults and severities based on dissolved gas analysis integrated with thermodynamics theory”, *IET Science, Measurement & Technology*, vol. 12, no. 3, pp. 388–394, 2018. DOI: 10.1049/iet-smt.2017.0450.

[199] O. E. Gouda, S. H. El-Hoshy, and H. H. E.L. - Tamaly, “Proposed three ratios technique for the interpretation of mineral oil transformers based dissolved gas analysis”, *IET Generation, Transmission & Distribution*, vol. 12, pp. 2650–2661. DOI: 10.1049/iet-gtd.2017.1927.

[200] Z. Qian, W. S. Gao, F. Wang, and Z. Yan, “A case-based reasoning approach to power transformer fault diagnosis using dissolved gas analysis data”, *European Transactions on Electrical Power*, vol. 19, pp. 518–530. DOI: 10.1002/etep.240.

[201] Y. Liang, Z. Zhang, K.-J. Li, and Y.-C. Li, “New correlation features for dissolved gas analysis based transformer fault diagnosis based on the maximal information coefficient”, *High Voltage*, vol. 7, no. 2, pp. 302–313, 2022. DOI: 10.1049/hve2.12136.

[202] H. Zeinoddini-Meymand and B. Vahidi, “Techno-economical lifetime assessment of power transformers rated over 50 MVA using artificial intelligence models”, *IET Generation, Transmission & Distribution*, vol. 10, no. 15, pp. 3885–3892, 2016. DOI: 10.1049/iet-gtd.2016.0480.

[203] C. Ding, Q. Ding, L. Feng, and Z. Wang, “Prediction model of dissolved gas in transformer oil based on VMD-SMA-LSSVM”, *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 17, no. 10, pp. 1432–1440, 2022. DOI: 10.1002/tee.23653.

[204] M. Varan and U. Yurtsever, “Multi-DGAS: A pattern based educational framework design for power transformers faults interpretation and comparative performance analysis”, *Computer Applications in Engineering Education*, vol. 26, no. 2, pp. 215–227, 2018. DOI: 10.1002/cae.21872.

[205] A. Nanfak, S. Eke, C. H. Kom, R. Mouangue, and I. Fofana, “Interpreting dissolved gases in transformer oil: A new method based on the analysis of labelled fault data”, *IET Generation, Transmission & Distribution*, vol. 15, no. 21, pp. 3032–3047, 2021. DOI: 10.1049/gtd2.12239.

[206] S. A.Wani, D. Gupta, Md. U. Farooque, and S. A. Khan, “Multiple incipient fault classification approach for enhancing the accuracy of dissolved gas analysis (DGA)”, *IET Science, Measurement & Technology*, vol. 13, no. 7, pp. 959–967, 2019. DOI: 10.1049/iet-smt.2018.5135.

[207] A. Chatterjee, R. Sarkar, N. K. Roy, and P. Kumbhakar, “Online monitoring of transformers using gas sensor fabricated by nanotechnology”, *International Transactions on Electrical Energy Systems*, vol. 23, pp. 867–875, 2013. DOI: 10.1002/etep.1675.

[208] J. Jiang and G. Ma, “Dissolved gases detection with optical methods”, *Optical Sensing in Power Transformers*, pp. 65–135, 2021. DOI: 10.1002/9781119765325.ch4.

[209] X. Tan, C. Guo, K. Wang, and F. Wan, “A novel two-stage Dissolved Gas Analysis fault diagnosis system based semi-supervised learning”, *High Voltage*, vol. 7, no. 4, pp. 676–691, 2022. DOI: 10.1049/hve2.12195.

[210] T. Yang, Y. Fang, C. Zhang, C. Tang, and D. Hu, “Prediction of dissolved gas content in transformer oil based on multi-information fusion”, *High Voltage*, vol. 9, no. 3, pp. 685–699, 2024. DOI: 10.1049/hve2.12408.

[211] C. Dai, Z. Liu, K. Hu, and K. Huang, “Fault diagnosis approach of traction transformers in high-speed railway combining kernel principal component analysis with random forest”, *IET Electrical Systems in Transportation*, vol. 6, no. 3, pp. 202–206, 2016. DOI: 10.1049/iet-est.2015.0018.

[212] X. Wang, Q. Li, R. Yang, C. Li, and Y. Zhang, “Diagnosis of solid insulation deterioration for power transformers with dissolved gas analysis-based time series correlation”, *IET Science, Measurement & Technology*, vol. 9, no. 4, pp. 393–399, 2015. DOI: 10.1049/iet-smt.2014.0074.

[213] S. I. Ibrahim, S. S. M. Ghoneim, and I. B. M. Taha, “DGALab: An extensible software implementation for DGA”, *IET Generation, Transmission & Distribution*, vol. 12, no. 18, pp. 4117–4124, 2018. DOI: 10.1049/iet-gtd.2018.5564.

[214] L. Zhang, G. Sheng, H. Hou, N. Zhou, and X. Jiang, “An adaptive fault diagnosis method of power transformers based on combining oversampling and cost-sensitive learning”, *IET Smart Grid.*, vol. 4, no. 6, pp. 623–635, 2021. DOI: 10.1049/stg2.12044.

[215] H. Niu *et al.*, “Advances in flexible sensors for intelligent perception system enhanced by artificial intelligence”, *InfoMat*, vol. 5, no. 5, p. e12412, 2023. DOI: 10.1002/inf2.12412.

[216] X. Wang, J. Yang, X. Yang, and X. Hu, “A novel study on activated carbon production based on artificial neural network model: An experimental and artificial intelligence method approach”, *International Journal of Energy Research*, vol. 46, no. 15, pp. 21480–21496, 2022. DOI: 10.1002/er.7857.

[217] O. E. Gouda, S. H. El-Hoshy, and H. H. El-Tamaly, “Proposed heptagon graph for DGA interpretation of oil transformers”, *IET Generation, Transmission & Distribution*, vol. 12, no. 2, pp. 490–498, 2018. DOI: 10.1049/iet-gtd.2017.0826.

[218] Md. M. Nezami *et al.*, “A novel artificial neural network approach for residual life estimation of paper insulation in oil-immersed power transformers”, *IET Electric Power Applications*, vol. 18, no. 4, pp. 477–488, 2024. DOI: 10.1049/elp2.12407.

[219] N. Khan and Dr. S. A. A. Taqvi, “Machine learning an intelligent approach in process industries: A perspective and overview”, *ChemBioEng Reviews*, vol. 10, no. 2, pp. 195–221, 2023. DOI: 10.1002/cben.202200030.

[220] J. Fan, F. Wang, Q. Sun, F. Bin, F. Liang, and X. Xiao, “Hybrid RVM–ANFIS algorithm for transformer fault diagnosis”, *IET Generation, Transmission & Distribution*, vol. 11, no. 14, pp. 3637–3643, 2017. DOI: 10.1049/iet-gtd.2017.0547.

[221] Y. Li, Y. Xu, X. Li, R. Li, J. Lin, and G. Zhang, “Addressing imbalance of sample datasets in dissolved gas analysis by data augmentation: Generative adversarial networks”, *IET Generation, Transmission & Distribution*, vol. 16, no. 22, pp. 4494–4504, 2022. DOI: 10.1049/gtd2.12610.

[222] Q. Hu, J. Mo, S. Ruan, and X. Zhang, “Fault diagnosis of oil-immersed power transformers using SVM and logarithmic arctangent transform”, *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 17, no. 11, pp. 1562–1569, 2022. DOI: 10.1002/tee.23678.
[223] X. Yang, W. Chen, A. Li, and C. Yang, “A hybrid machine-learning method for oil-immersed power transformer fault diagnosis”, *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 15, no. 4, pp. 501–507, 2020. DOI: 10.1002/tee.23081.
[224] Y. Wang, “Application of improved support vector machine model in fault diagnosis and prediction of power transformers”, *Advanced Control for Applications: Engineering and Industrial Systems*, vol. 6, no. 4, p. e170, 2024. DOI: 10.1002/adc2.170.
[225] Y. Zheng, H. Yao, J. Sheng, W. He, X. Sun, W. Wang, and J. Zhan, “Case-based power transformer diagnose model using nonlinear mapping of oil chromatography”, *The Journal of Engineering*, vol. 2019, no. 16, pp. 715–719, 2019. DOI: 10.1049/joe.2018.8372.
[226] H. Hu, X. Ma, and Y. Shang, “A novel method for transformer fault diagnosis based on refined deep residual shrinkage network”, *IET Electric Power Applications*, vol. 16, no. 2, pp. 206–223, 2022. DOI: 10.1049/elp2.12147.
[227] C. Ding, Q. Ding, Z. Wang, and Y. Zhou, “Fault diagnosis of oil-immersed transformers based on the improved sparrow search algorithm optimised support vector machine”, *IET Electric Power Applications*, vol. 16, no. 9, pp. 985–995, 2022. DOI: 10.1049/elp2.12204.
[228] S. A. Wani, S. A. Khan, D. Gupta, and Md. M. Nezami, “Diagnosis of incipient dominant and boundary faults using composite DGA method”, *International Transactions on Electrical Energy Systems*, vol. 27, p. e2421, 2017. DOI: 10.1002/etep.2421.
[229] T. Kari *et al.*, “Hybrid feature selection approach for power transformer fault diagnosis based on support vector machine and genetic algorithm”, *IET Generation, Transmission & Distribution*, vol. 12, no. 21, pp. 5672–5680, 2018. DOI: 10.1049/iet-gtd.2018.5482.
[230] Y. Zhang *et al.*, “Power transformer fault diagnosis considering data imbalance and data set fusion”, *High Voltage*, vol. 6, no. 3, pp. 543–554, 2021. DOI: 10.1049/hve2.12059.
[231] N. Mahmoudi, M. H. Samimi, and H. Mohseni, “Experiences with transformer diagnosis by DGA: Case studies”, *IET Generation, Transmission & Distribution*, vol. 13, no. 23, pp. 5431–5439, 2019. DOI: 10.1049/iet-gtd.2019.1056.
[232] S. Li, H. Ma, T. Saha, and G. Wu, “Bayesian information fusion for probabilistic health index of power transformer”, *IET Generation, Transmission & Distribution*, vol. 12, no. 2, pp. 279–287, 2018. DOI: 10.1049/iet-gtd.2017.0582.
[233] S. Li and J. Li, “Condition monitoring and diagnosis of power equipment: Review and prospective”, *High Voltage*, vol. 2, no. 2, pp. 82–91, 2017. DOI: 10.1049/hve.2017.0026.
[234] W. Lu, C. Shi, H. Fu, and Y. Xu, “Research on transformer fault diagnosis based on ISOMAP and IChOA-LSSVM”, *IET Electrical Power Applications*, vol. 17, no. 6, pp. 773–787, 2023. DOI: 10.1049/elp2.12302.
[235] M. M. F. Darwish *et al.*, “A new technique for fault diagnosis in transformer insulating oil based on infrared spectroscopy measurements”, *High Voltage*, vol. 9, no. 2, pp. 319–335, 2024. DOI: 10.1049/hve2.12405.
[236] O. Ozgonenel and S. Karagol, “Power transformer protection based on decision tree approach”, *IET Electric Power Applications*, vol. 8, no. 7, pp. 251–256, 2014. DOI: 10.1049/iet-epa.2013.0407.
[237] H. Shi and M. Chen, “A two-stage transformer fault diagnosis method based multi-filter interactive feature selection integrated adaptive sparrow algorithm optimised support vector machine”, *IET Electric Power Applications*, vol. 17, no. 3, pp. 341–357, 2023. DOI: 10.1049/elp2.12270.
[238] X. Huang, X. Huang, B. Wang, and Z. Xie, “Fault diagnosis of transformer based on modified grey wolf optimization algorithm and support vector machine”, *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 15, no. 3, pp. 409–417, 2020. DOI: 10.1002/tee.23069.
[239] Y. Wu, X. Sun, B. Dai, P. Yang, and Z. Wang, “A transformer fault diagnosis method based on hybrid improved grey wolf optimization and least squares-support vector machine”, *IET Generation, Transmission & Distribution*, vol. 16, no. 10, pp. 1950–1963, 2022. DOI: 10.1049/gtd2.12405.
[240] E. Baker, “DGA-based hybrid intelligent system for fault diagnostics of power transformers”, M.S. thesis, Dept. Electrical Electronics Eng., Marmara Univ., Istanbul, Turkiye, 2022.
[241] E. Moradi, “A data-driven based robust multilayer perceptron approach for fault diagnosis of power transformers”, in *Proc. of 2024 20th CSI International Symposium on Artificial Intelligence and Signal Processing (AISP)*, 2024, pp. 1–5. DOI: 10.1109/AISP61396.2024.10475257.
[242] A. Abdo *et al.*, “Hybrid model of power transformer fault classification using C-set and MFCM – MCSVM”, *CSEE Journal of Power and Energy Systems*, vol. 10, no. 2, pp. 672–685, 2024. DOI: 10.17775/CSEEJPES.2020.04010.
[243] G. S. Patil, U. S. Patil, and P. P. Shinde, “Enhancing power transformer reliability through machine learning-based fault prediction using Dissolved Gas Analysis”, in *Proc. of 2024 Third International Conference on Power, Control and Computing Technologies (ICPC2T)*, 2024, pp. 72–76. DOI: 10.1109/ICPC2T60072.2024.10474728.
[244] S. Seifeddine, B. Khmais, and C. Abdelkader, “Power transformer fault diagnosis based on dissolved gas analysis by artificial neural network”, in *Proc. of 2012 1st International Conference on Renewable Energies and Vehicular Technology*, 2012, pp. 230–236. DOI: 10.1109/REVET.2012.6195276.
[245] A. Dhini, A. Faqih, B. Kusumoputro, I. Surjandari, and A. Kusiak, “Data-driven fault diagnosis of power transformers using Dissolved Gas Analysis (DGA)”, *International Journal of Technology*, vol. 11, no. 2, p. 388, 2020. DOI: 10.14716/ijtech.v11i2.3625.
[246] Z. Du, F. Zhang, Z. Ge, X. Han, L. Li, and J. Wen, “Analysis of abnormal dissolved gas in 220 kV transformer oil by David Pentagon method”, in *Proc. of the 18th Annual Conference of China Electrotechnical Society*, 2024, pp. 268–275. DOI: 10.1007/978-981-97-1420-9_29.
[247] A. R. G. Castro and V. Miranda, “Knowledge discovery in neural networks with application to transformer failure diagnosis”, *IEEE Transactions on Power Systems*, vol. 20, no. 2, pp. 717–724, 2005. DOI: 10.1109/TPWRS.2005.846074.