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Hybrid Multilayer Perceptron Neural Network for Transformer Health Index Monitoring

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ABSTRACT

Power transformers are critical to electrical systems, requiring accurate health monitoring to ensure reliability and prevent failures. Traditional assessment methods often fail to capture complex variable interactions, resulting in suboptimal maintenance strategies. This study introduces a hybrid multilayer perceptron (HMLP) neural network for transformer health index (HI) monitoring, using approximately 500 data points from the Klang Valley, including gas formation data. The HMLP is benchmarked against classifiers such as multilayer perceptron (MLP), K-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM), outperforming them with 92.35% accuracy and a mean squared error (MSE) of 0.78. Additionally, three training algorithms; Backpropagation (BP), Levenberg-Marquardt (LM) and Bayesian Regularization (BR) were tested, with the BR algorithm achieving the best performance at 94.13% accuracy and an MSE of 0.39. This research highlights the potential of the HMLP network, particularly when trained with BR, to revolutionize transformer maintenance by enabling precise THI predictions, facilitating proactive interventions and ensuring power system reliability.

1. Introduction

Power transformers are the most valuable assets in a power grid and as a result, they account for a significant portion of the total investment in a power delivery system. Since a malfunctioning transformer that leads to malfunctions might result in a power outage, which can result in plant owners experiencing significant financial losses because of the inability to produce energy, planned observations and general maintenance are required as preventive action consideration [1,2].

In addition, faulty transformers would result in potentially hazardous conditions, such as noise pollution, power loss and combustion, all of which would discharge smoke from the transformers. Therefore, guaranteeing the health of a transformer if it fails to function properly can lead to a big issue.

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Power transformers are working at levels of load that are reaching perilously close to their nominal limitations because of the continual growth in demand for load, which makes it more probable that the transformers may collapse or fail to deliver the operation. The use of a neural network to address the issue of health monitoring for power transformers is the primary focus of this research. Therefore, discovering the issue with the transformer as quickly as possible is essential to maintain the maximum possible balance between the expenses of maintenance, the costs of making capital expenditures and the costs of maintaining a safe working environment [3].

Towards the end of the 19th century, calculating the HI evolved into a procedure that is proving to be more helpful than ever before when it comes to determining the condition of transformers. The HI is a method that is quick and accurate for determining the condition of power transformers by considering various parameters. The HI was arrived at by considering and combining several different elements during the process. These contained information describing a transformer's current and other test results, expert opinions and data gathered from field inspections. To reduce costs, it is vital to cut down on the number of required experiments that must be performed. For the goal of HI prediction, artificial neural networks (ANN) are used and the feature-based exhaustive technique is applied to get rid of the tests that are identified to be the least significant [4].

Nowadays, the rapid development of computer science and data processing has led to the creation of new HI approaches for the analysis of huge data that are based on machine learning algorithms. These new methods have been made possible because of the quick pace of technological improvement [5]. An ANN-based on HI technique was explored and it employed data from dissolved gases analysis, furan testing and oil testing to evaluate the overall health state of several transformers already in optimum service [6]. One of power provider in Malaysia has been following this technique, which entails documenting the amount of gas that is present in the transformer oil.

This practice has been in use for some time and was presented earlier in the discussion. After that, this oil will be taken to a laboratory, where it will be computed and examined to determine the quantity of Total Dissolve Combustible Gas (TDCG) and then the type of condition of the transformer will be determined to be either condition 1, 2, 3 or condition 4. Due to a lack of qualified specialists working for the power provider who can analyses the transformer HI, this process is fraught with difficulties and should be avoided at all costs. Because of the way that is utilized, calculating the transformer's HI is created to be a more difficult and time-consuming process. After that, the power provider will be responsible for coordinating the annual scheduling of maintenance on transformers, which will be done on a rotating basis. This will be a constant problem for older transformers requiring preventive action. The research utilised ANN to monitor the power transformer HI using the data that was sourced based on 50 transformers within Klang Valley. The data has been pre-processed and analysed using MATLAB Neural Network toolbox, to create and stimulate the neural network to find the optimal approach for the data provided.

2. Literature Review

Generally, the transformer HI index can be considered a measurement or evaluation of the state and performance of the transformer. In most cases, it requires inspecting several properties, including temperature, oil quality, the condition of the insulation, winding resistance and further diagnostic tests. By studying these characteristics, professionals and researchers can evaluate the overall health of a transformer as well as the remaining useful life of the device. This enables them to identify potential failures and, as a result, prepare for maintenance or replacement processes. The transformer HI is a single factor that utilises the data from operating observations, field inspections and laboratory testing to create a valid asset management decision for transformers. Rediansyah *et al.,* [7] mentioned this decision may be used to keep transformers in good working order.

The identification of the variables that have the most significant impact on the transformer HI has also attracted the attention of a substantial number of researchers. The levels of the data source and diagnostics are the ones that are accountable for simulating the most important causes of uncertainty. The available data sources are influenced by measurement uncertainties, which present themselves as a range of faults including measurement and quantisation mistakes. These flaws can be found in the accessible data sources. Whether correct knowledge or stochastic uncertainties are present, modelling uncertainties have an impact on the diagnostics models that are built. This is the case regardless of which type of uncertainty is present. Figure 1 illustrates the structure for the transformer HI that was built and implemented.

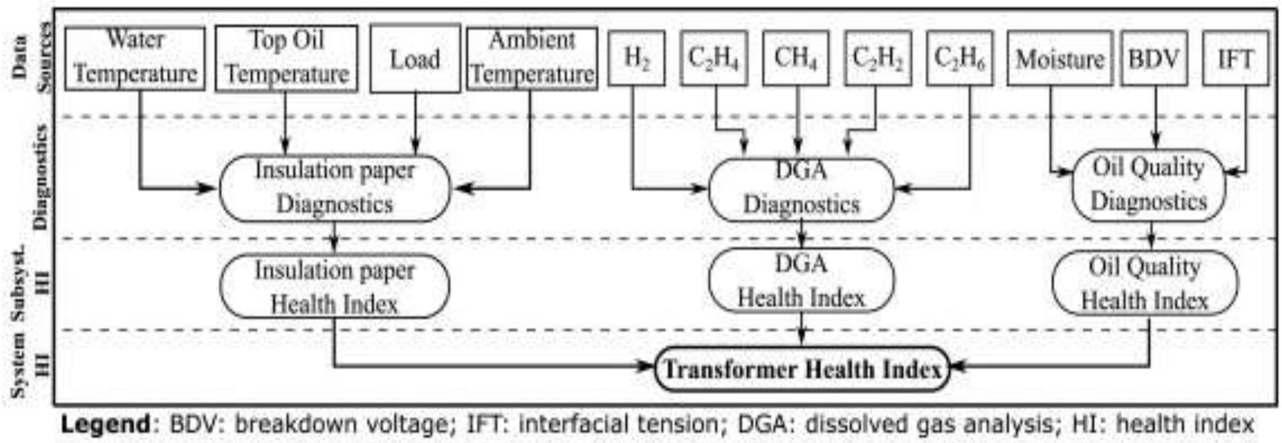

Fig. 1. Transformer HI soft computing framework [8]

In addition, the effect of several uncertainty sources, which are examined across various transformer subsystems, is propagated up to the level of the transformer HI. This helps to inform the final decision-making process better and makes it appropriate for application in the context of systems surrounded by measurement and process uncertainties. Furthermore, it makes it suitable for use in the context of decision-making processes that are surrounded by uncertainty. Dissolve gas analysis (DGA) is a diagnostic method frequently used to determine whether electrical power transformers are in healthy operating condition. Taking readings and conducting studies of gas concentrations that have been dissolved in the insulating oil of a transformer is required to carry out this task. These gases are produced inside the transformer due to several faults and abnormalities on the device's interior. These flaws and irregularities can be found inside the device. The DGA is one of the diagnostic methods utilised for determining the condition of transformers regularly [9]. This is since previous experience has demonstrated that the DGA is an effective tool [10].

If a transformer experiences problems such as overheating, electrical arcing, partial discharge or deterioration of the insulation, particular gases are expelled into the oil that serves as the medium for the transformer's insulation. By evaluating the quantities and types of gases in Table 1, specialists can gather substantial insights into the internal condition of the transformer and identify potential problems. When analysing the concentration levels and ratios of the gases, as well as other criteria such as the quality of the oil and the results of electrical tests, specialists can evaluate the overall health of the transformer, identify specific defect types and estimate the urgency and kind of maintenance or repairs that are required.

When it comes to determining the condition of transformers as taken from a previous study by Guo *et al.,* [11], the DGA method is one that is both widely utilised and helpful. This is a result of the fact that it enables the early diagnosis of prospective problems, the prediction of defects and the proactive planning of maintenance to avoid the risk of failures and costly downtime. Moreover, this is made possible because it can be done in real-time. A DGA is performed on the transformer as part of the standard and customary periodic maintenance to determine its age and the extent of degradation it experienced [12].

Table 1
The most common gases analysed in DGA

Type of Gaseous	Fault Type
Hydrogen (H_2)	Elevated levels of hydrogen indicate the presence of electrical arcing, which may suggest insulation breakdown or localized overheating.
Methane (CH_4) & Ethane (C_2H_6)	These gases are typically associated with thermal and electrical faults, such as overheating of solid insulation or oil degradation.
Ethylene (C_2H_4) & Acetylene (C_2H_2)	These gases are primarily generated due to severe electrical faults like arcing, corona discharge or insulation breakdown.
Carbon Monoxide (CO) & Carbon Dioxide (CO_2)	These gases can be indicative of overheating, combustion or ageing processes.
Oxygen (O_2)	The presence of oxygen can suggest leakage into the transformer, which can degrade the insulation and increase the risk of further faults.

Techniques drawn from the field of artificial intelligence were utilised to arrive at an estimation of the HI of the transformers. The typical development of an ANN-based HI model resembles the timeline shown in Figure 2, which may be found here. The application of artificial intelligence to the process of evaluating the condition of power transformers is particularly helpful for analysing large datasets related to transformers [13].

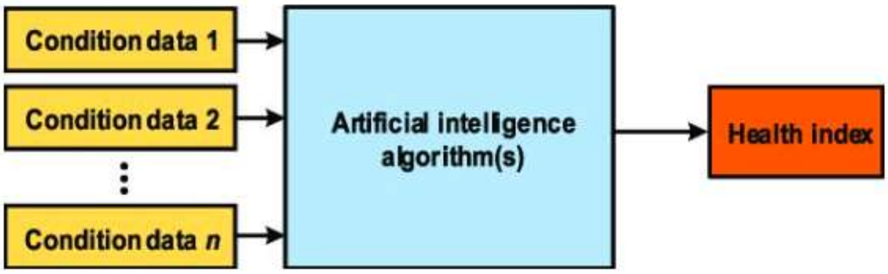

Fig. 2. Assessing transformer HI using ANN principle [13]

When calculating transformer HI, several different types of data are considered, including the transformer's age, data from operations and data from on-site tests. Guo *et al.,* [11] highlighted the rate at which the transformer ages are determined not only by the length of time that it has been in use but also by the amount of time that it was designed to remain in service [11]. The data from the operation of the transformer contain information on its loading as well as the level of pollution it produced. These specifics offer an indication of the primary condition of the transformer and constitute an indispensable part of the condition assessment of the device. Furthermore, the outcomes of on-site tests can provide a reflection of the condition the transformer was in at the time of the test and as a result, they are vital to the process of evaluating the condition of the transformer.

Sun *et al.,* [14] delivered a novel multi-attribute decision-making model for evaluating the condition of transformers. The model makes use of fuzzy computerization set theory, game theory and modified evidence combination extended by D numbers. The fuzzy computerization set theory is incorporated into this paradigm. The model includes several processes, one of which is the construction of a framework for the evaluation of the current condition of the transformer. Other steps in the model include the establishment of a fuzzy membership matrix and the determination of evaluation grades. The total weight is determined through the application of game theory and the results of the final evaluation are derived by the application of the modified evidence combination to the evidence that has been increased by D numbers as taken from a previous study by Sun *et al.,* [14]. The proposed model is demonstrated to be accurate by investigating on a real transformer and comparing the findings to those obtained from the established practice. According to the data, the model can effectively identify the current state of health of the transformer.

ANN is a branch of artificial intelligence as it based on brain function. Based on the principles of brain, the artificial neural network designed to resemble a brain operation such as structure building, learning techniques and operating techniques. Figure 3 shows diagram of the nonlinear neuron model. Salim *et al.,* [15] highlighted that their goal was to imitate the operation of an ANN to calculate the HI of a transformer. To compute the HI of the transformer, a feedforward artificial neural network was utilised alongside an actual measurement of the operational transformer. Additionally, Al Mhdawi *et al.,* [16] and Jamil *et al.,* [17] suggested the use of a prediction system that is founded on an algorithm for an ANN.

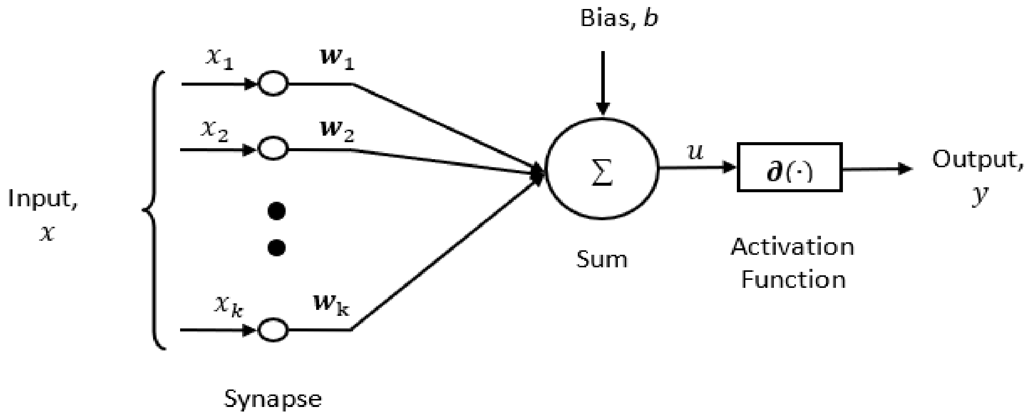

Fig. 3. Nonlinear neural model

This system, which we call distribution transformer failure prediction, would be installed on the management plane for periodic prediction based on real-time sensor traffic to our proposed cloud. This prediction would be based on data collected by our proposed cloud. This would make it possible to make forecasts on a periodic basis. Prior works utilised the ANN methodologies and fuzzy logic techniques respectively, [18-20], to classify the transformer state by applying the standard condition tests. These classifications were based on the HI value.

The existence of multiple layers of units is a defining characteristic of the MLP (MLP) network architecture. Every node in every layer connected to every other node in the layers below it in the completely interconnected networks that were taken into consideration [12]. An MLP is constructed from three layers: an input layer, hidden layers that are composed of hidden units and an output layer. The output of the MLP network is given by Eq. (1),

$$\hat{y}_k(t) = \sum_{j=1}^{n_h} w_{jk}^2 \partial\left(\sum_{i=1}^{n_i} w_{ij}^1 x_i^0(t) + b_j^1\right) \tag{1}$$

for $1 \le j \le n_h$ and $1 \le k \le m$

Where n_h denotes hidden nodes and m denotes the number of network outputs while $\boldsymbol{\partial}(\cdot)$ is the activation function with the sigmoid used to activate the MLP network. The weights are unknown and they need to converge the optimum values to minimise the prediction error, with $y_k(t)$ being the actual output from the system while $\hat{y}_k(t)$ is the predicted output.

There have been several modified versions based on conventional MLP networks, such as the addition of a linear connection directly from the input layer to the output layer to form a new network known as HMLP network. The HMLP networks can improve the accuracy of results compared to conventional MLP networks. The ability of ANNs to make good predictions is highly dependent on the training algorithms used and the design of the structure [17]. The direct linear connection between the input and the output layers has been applied to improve the efficiency and generalization of conventional nonlinear neural networks [17-20], resulting in the HMLP network. Naturally, improved training algorithms were also sought to deal further improves performance.

An MLP neural network is a highly nonlinear functional structure that can be trained to implement a desired input-output mapping [20,21]. They also stated that using a nonlinear network, such as MLP to model a linear system will not produce an accurate prediction. To do that, HMLP network does cope well with linear systems owing to the direct input to output connections, represented by the dashed line in Figure 4. The figure consists of a set of an input layer, a single hidden layer and an output layer.

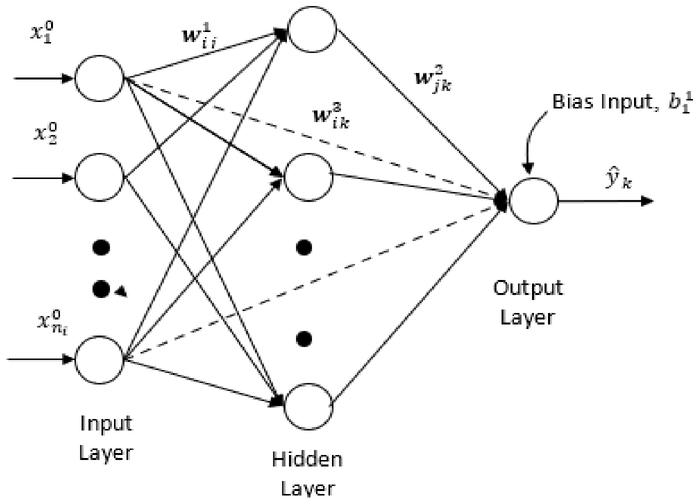

Fig. 4. HMLP architecture with one hidden layer

The output of the HMLP network is given by Eq. (2),

$$\hat{y}_k(t) = \sum_{j=1}^{n_h} w_{jk}^2 \partial\left(\sum_{i=1}^{n_i} w_{ij}^1 x_i^0(t) + b_j^1\right) + \sum_{i=1}^{n_i} w_{ik}^3 x_i^0(t) \tag{2}$$

$for\ 1 \leq j \leq n_h$ and $1 \leq k \leq m$

Where w_{ik}^3 represents the weight of the additional linear connection between the input and output layers, n_h are the hidden nodes while m is the number of outputs of the network. $\boldsymbol{\partial}(\cdot)$ is the activation function with the sigmoid activation function chosen to activate the HMLP network in this case. The weights w_{ij}^1, w_{jk}^2, w_{ik}^3 and threshold b_j^1 are unknown variables and they need to converge to optimum values to minimize the prediction error defined as in Eq. (3),

$$e_k(t) = y_k(t) - \hat{y}_k(t) \tag{3}$$

with $y_k(t)$ being the actual output from the system while $\hat{y}_k(t)$ is the predicted output.

3. Methodology

The research methodology implemented is called the Integration of the KGM into a system for analysing transformer data received through DGA. The conditions that are outlined in Table 2 have served as the organizing principle for this data. These conditions are determined by performing the calculation known as the TDCG, which involves summing the various gas concentrations that are presented in Table 3. After then, the TDCG is used to establish the conditions that the data should be structured according to and it does this by using the data itself. Following this step, the values that were derived from the TDCG are utilized in the sorting process for the data.

Table 2
Gasses involved in KGM

Type of Gas	Formula
Hydrogen	H_2
Methane	CH_4
Acetylene	C_2H_2
Ethylene	C_2H_4
Ethane	C_2H_6
Carbon Monoxide	CO
Carbon Dioxide	CO_2

The TDCG limit concentration that was discovered in Table 3 was utilized as a point of reference to classify the collected data into one of four separate categories. The label "Condition 1" refers to a transformer that meets all standards and does not include any errors. The term "Condition 2" refers to a state that is acceptable despite the presence of some minor faults and can still be utilized, even though there are a few of these concerns. The item is in a poor state and problems have been found that need to be fixed or maintained within the next six months. This condition is denoted by the designation "Condition 3." Finally, "Condition 4" refers to an urgent scenario in which serious defects need to be quickly fixed within the next three months or as soon as possible.

Table 3
Limit assigned as input

TDCG Limit	Condition
720	1
721-1920	2
1921-4630	3
>4630	4

As its input, a HMLP network uses the data that is supplied by the power provider in company. Neurons that are connected to one another and have weights and biases that have been predetermined make up the HMLP network.

It is determined how many hidden layers there are, in addition to the activation strategies that should be utilised. Several distinct approaches, including BP from a previous study by Mat *et al.,* [21], BR [22] and LM [23], are applied in the process of training the model. Simulations are run to ensure that the findings can be trusted and this helps ensure that they are accurate. Research flow chart for this project is depicted as follow in Figure 5. The data transmission process that takes place inside a HMLP network is referred to as "feedforward." This occurs as information goes from the input layer to the output layer. This is the term that is utilised when referring to the procedure that is being carried out. Depending on the implementation, an MLP may have one or more layers between its input and output layers. This number of levels might vary depending on the model design.

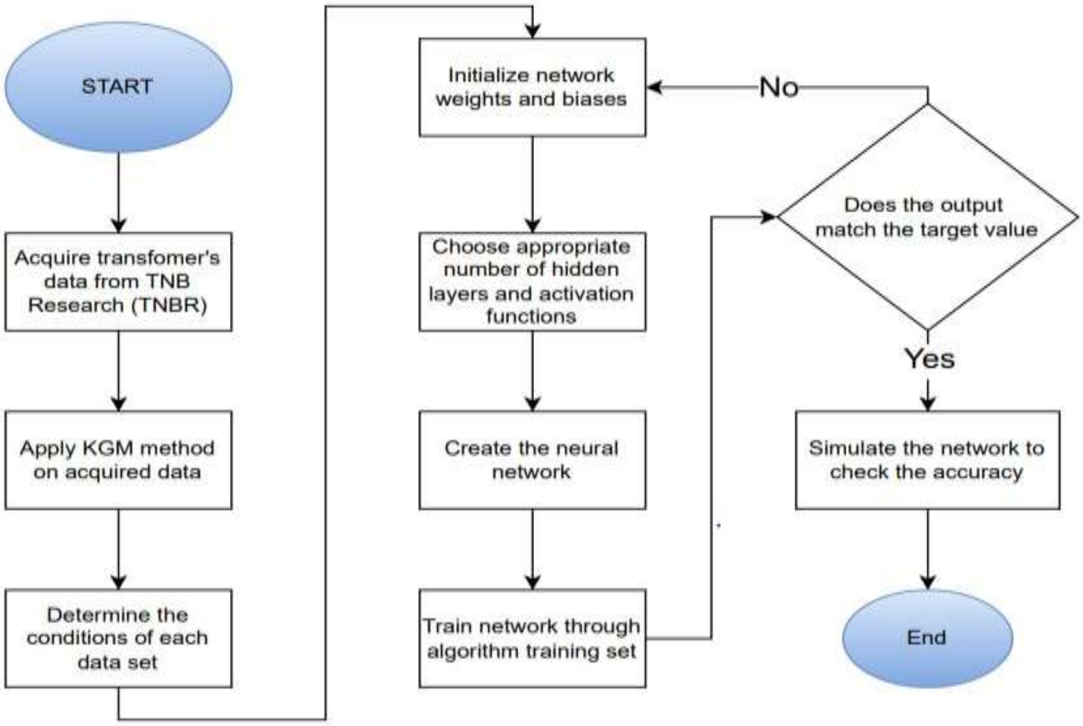

Fig. 5. MLP application to assess HI using ANN

MSE is a metric that examines the average squared difference between the target values that are created in the training samples and the output values that are predicted by an ANN. The MSE is another name for the term. If the MSE values go down, this suggests that the accuracy of the forecast is getting better. The performance of neural networks now can be accurately characterised as trustworthy and consistent. The accuracy of the detection data can be assessed by taking the number of data instances that have been correctly detected and dividing that number by the total number of data instances that belong to the class. This gives the percentage of data instances that have been correctly detected. The MSE is calculated by multiplying the difference between the identified output data and the actual output data by a factor of four. The method that is used to calculate the average deviation of each data set involves putting up the squared differences that were discovered in the previous phase as in Eq. (5),

$$MSE = \frac{(\sum_{n=1}(y(t)-\hat{y}(t))^2)}{n} \tag{5}$$

with $y(t)$ is the output forecast data while the $\hat{y}(t)$ actual output data and n is the number of data used. This assessment is based on the model's capacity to attain the highest possible level of prediction accuracy while simultaneously minimising the MSE.

4. Results and Discussion

The KGM is going to be implemented and the goal of this study is to figure out how to achieve it in the most effective way possible. This study's objective is to assess and compare the efficacy of a variety of training algorithms in relation to the morphology of the parameters that are taken into consideration. For evaluating the effectiveness of the network, metrics like accuracy and MSE are utilised. Additionally, other methods for diagnosing DGA will be researched as part of this research. The expected output values are shown in Table 4 as a percentage of the accuracy and MSE of several classifier such as KNN, LDA, MLP and SVM.

Table 4
The performance of several classifier

Classifier	Accuracy	MSE
KNN	88.32%	0.89
HMLP	92.53 %	0.78
MLP	90.67%	0.92
LDA	72.82%	0.93
SVM	86.42%	0.87

A comparison of the effectiveness of various classifiers in one task is shown in Table 4. Given its accuracy of 90.76% and MSE of 0.92, the MLP classifier performs better than the others, according to the data. Comparing the MLP classifier to the other classifiers assessed in the study, it performs better in terms of accuracy and MSE. However, with additional linear connection between input layer and output layer may gain better performance with 92.53% of accuracy and 0.78 of MSE. The performance is improved better than conventional MLP network. KNN and SVM classifiers come in second and third place, respectively, after MLP. KNN is 86.32% accurate and has an MSE of 0.89, while SVM is 86.42% accurate and has an MSE of 0.87. However, with an accuracy of just 72.82% and an MSE of 0.73, the LDA classifier appears to perform worse than the other classifiers. It appears that the LDA classifier might not be a good fit for the task that is being assessed in this study.

The findings in Table 4 offer insightful information on the advantages and disadvantages of various classifiers in relation to the specified task. Based on its high accuracy and low MSE, the HMLP classifier comes out as the best solution for this classification task, making it a viable alternative. The HMLP classifier has been chosen for more analysis due to its higher performance in Table 4. Three alternative algorithms such as BP, LM and BR training algorithm have been employed to train the HMLP. As illustrated in Table 5, each training algorithm may produce different prediction outcomes. The results of using the three training procedures with the HMLP classifier are probably shown in Table 5, along with the related prediction outputs. Accuracy, MSE or other performance indicators used for evaluation could be the outcome of the prediction. Because different training algorithms have varied optimisation strategies, convergence behaviours and capacities to handle complicated data patterns, variances in prediction results are to be expected. While LM and BR are sophisticated optimisation approaches renowned for effectively handling non-linear and ill-conditioned problems, BP is a well-known and commonly utilised algorithm.

Table 5
The performance of MLP with different training algorithm

Training algorithm	Accuracy	MSE
BP	81.28%	0.62
BR	94.13%	0.39
LM	92.98%	0.71

The performance of several training techniques used to train the HMLP network is provide in Table 5. What stands out in this table is the BR algorithm performs best, with a 94.13% accuracy prediction and an MSE of 0.39. BR outperforms the other training methods assessed in terms of prediction accuracy and has a lower MSE. The accuracy and MSE of the LM algorithm, which ranks second to BR in performance, are 92.98% and 0.71, respectively. Despite slightly worse performance than BR, LM still offers competitive accuracy and MSE values. The BP algorithm, in contrast, seems to perform worse than BR and LM. Only 81.28% accuracy and an MSE of 0.62 are achieved by BP. Lower prediction accuracy and greater MSE appear to be the results of BP maybe not being suitable for the job or dataset being examined. The BR algorithm comes out as the best option for training the MLP network based on the findings in Table 5, having the highest accuracy and lowest MSE. The performance of the MLP classifier is greatly influenced by the choice of the training method and these findings imply that BR is more appropriate for the task at hand than LM and BP.

5. Conclusions

The aim of the study is to evaluate the accuracy, generalizability and reliability of classifiers in predicting power transformer health indices. Understanding how these networks operate enables the development of more accurate and trustworthy methods for determining the health of transformers, which results in better maintenance strategies, enhanced dependability and better performance of power systems. This research suggests a unique DGA method that would increase the diagnosis accuracy of transformer failures by utilising an MLP network classifier. This method applies the MLP network performance for the HI of the power transformer. The six main flammable dissolved gas concentrations used as an input to the classifier to determine the transformer failure type were hydrogen, ethane, methane, carbon monoxide, ethylene and acetylene. The KNN, MLP, LDA and SVM classifiers have already been used to train the data. The ppm and percentage concentrations of five dissolved gases were calculated. The MLP neural network trained using the BR training technique has the highest percentage, scoring BR 94.13% on accuracy and 0.39 on MSE, respectively.

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