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A Comparative Study of Machine Learning Classifiers in Oil-Immersed Power Transformer Fault Diagnosis

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Abstract

The most common fault diagnosis method for oil-immersed power transformers is dissolved gas analysis (DGA). Doernenburg ratios, Rogers ratios, IEC (International Electrotechnical Commission) ratios, and Duval's triangle are conventional DGA techniques for insulating oil in power transformers. In this study, Scikit-learn known as a popular open-source free machine learning tool for Python programming language has been used to develop different machine learning (ML) classifiers to effectively detect defects in oil-immersed power transformers. These classifiers are Decision Trees, Support Vector Machines, Gaussian Naive Bayes, k-Nearest Neighbours, Random Forests, and Multi-Layer Perceptron. The input vector of each classifier has been formed by Doernenburg ratios, Rogers ratios, IEC ratios, and CSUS (California State University Sacramento) method. After these classifiers are completely trained, unseen DGA data sets are then used to evaluate their performances. Based on a statistical analysis, the study can indicate the most effective type of the input vector and ML classifier for precisely detecting faults in power transformers.

Keywords: Power transformers, dissolved gas analysis, fault diagnosis, machine learning.

1. Introduction

Power transformers are electrical equipment widely used in power production, transmission, and distribution systems. Incipient power transformer faults usually cause electrical and thermal stresses in insulating materials. Due to these stresses, insulating materials can degrade or break down, and several gases are released. Therefore, the analysis of these dissolved gases can provide useful information on fault conditions and the types of materials involved. Dissolved gas analysis (DGA) of power transformer insulating oil is a well-known technique for monitoring and diagnosing power transformer health [1].

Conventional analysis techniques of dissolved gases can be performed by analysing different gas concentration ratios (Doernenburg ratios, Rogers ratios, and Duval's triangle method) [2, 3]. Artificial intelligence (AI)-based methods have been introduced to improve the diagnosis accuracy and remove the inherent uncertainty in DGA. These methods have been proposed with explorations of artificial neural networks (ANNs) [4, 5], fuzzy logic (FL) [6, 7], support vector machines (SVM) [8, 9], decision trees (DTs) [10], and K-nearest neighbours (k-NNs) [11]. Scikit-learn is well-known as a popular machine learning (ML) library for classification, regression, and clustering problems and is widely used with the Python programming language.

Classification problems can be solved using one of the following advanced ML algorithms: decision tree (DT), support vector machine (SVM), K-nearest neighbours (k-NN), random forest (RF), and Multi-Layer perceptron (MLP). In this research, six ML algorithms have been applied to the power transformer fault classification using available published data from the DGA for power transformers [12]. The paper is organised as follows: Section 2 describes the conventional methods of DGA for oil-insulating power transformers. The main features of ML classifiers are presented in Section 3. The details of power transformer fault classification are described in Section 4. Results and discussion are presented in Section 5. Finally, Section 6 is the conclusion of this research.

2. Conventional Methods of DGA for Power Transformer Insulating Oil

Electrochemical, thermal, and evaporative breakdown are the primary contributors to gas generation inside a power transformer that is in operation. Bonds between carbon and hydrogen, and carbon and carbon are broken in fundamental chemical processes. These gases include hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), and ethane. Typically, this event can produce active hydrogen atoms and hydrocarbon fragments (C_2H_6). With cellulose insulation, methane (CH_4), hydrogen (H_2), monoxide (CO), and carbon dioxide can be produced via heat breakdown or electrical faults

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(CO_2). These gases are commonly referred to as 'key gases'.

The first step in analysing DGA data after obtaining samples of transformer insulating oil is to calculate the concentration (in ppm) of each important gas. Once critical gas concentrations exceed the usual range, analytical procedures should be employed to identify any potential transformer defects. These methods entail computing important gas ratios and comparing those ratios to recommended limits. Doernenburg ratios, Rogers ratios, and IEC ratios like CH_4/H_2, C_2H_2/C_2H_4, C_2H_2/CH_4, C_2H_6/C_2H_2, and C_2H_4/C_2H_6 are the most used approaches. Table 1 and Table 2 display the proposed upper and lower bounds for the Doernenburg ratios approach and the Rogers ratios method, respectively.

The total amount of the three major gases methane (CH_4), acetylene (C_2H_2), and ethylene (C_2H_4) is used in Duval's triangle technique. The percentage associated with each gas is then calculated by dividing its concentration by the sum of the amounts of the three gases. Then, to determine a diagnosis, these values are plotted in Duval's triangle as seen in Fig. 1. Sections within the triangle designate: partial discharge (PD), low-energy discharge (D1), high-energy discharge (D2), thermal fault below 300 ºC (T1), thermal fault between 300 ºC and 700 ºC (T2), thermal fault above 700 ºC (T3).

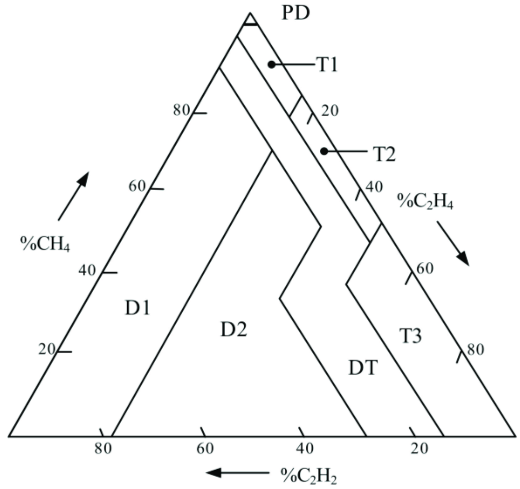

Fig. 1. Duval's triangle.

Table 1. Suggested limits of Doernenburg ratios method.

Suggested fault diagnosis	$R_1 = \frac{CH_4}{H_2}$	$R_2 = \frac{C_2H_2}{C_2H_4}$	$R_3 = \frac{C_2H_2}{CH_4}$	$R_4 = \frac{C_2H_6}{C_2H_2}$
Thermal decomposition	>1.0	< 0.75	< 0.3	> 0.4
Partial discharge	< 0.1	Not significant	< 0.3	> 0.4
Arcing	>0.1 - <1.0	> 0.75	> 0.3	< 0.4

Table 2. Suggested limits of Rogers ratios method.

Suggested fault diagnosis	$R_1 = \frac{CH_4}{H_2}$	$R_2 = \frac{C_2H_2}{C_2H_4}$	$R_5 = \frac{C_2H_4}{C_2H_6}$
Unit normal	> 0.1 - <1.0	< 0.1	< 1.0
Low-energy density arcing	< 0.1	< 0.1	< 1.0
Arcing-high energy discharge	0.1 - 1.0	0.1 - 3.0	> 3.0
Low temperature thermal	>0.1 - <1.0	< 0.1	1.0 - 3.0
Thermal < 700 ºC	> 1.0	< 0.1	1.0 - 3.0
Thermal > 700 ºC	> 1.0	< 0.1	➢ 3.0

3. Machine Learning Classifiers

The following machine learning (ML) algorithms can be used to effectively diagnose faults of oil-immersed power transformers:

- Decision Tree (DT) classifier
- Support Vector Machine (SVM) classifier
- Naive Bayes (NB) classifier
- The k-Nearest Neighbours (k-NN) classifier
- Random Forests (RF) classifier
- Multi-Layer Perceptron (MLP) classifier

3.1. Decision Tree Classifier

Decision Trees belong to non-parametric supervised learning methods and are used for classification and regression tasks. In this learning method, a model is created to predict the value of a target variable based on learning simple decision rules from the data features. The advantages of decision trees are:

- It is simple to understand and to interpret as trees can be easily visualised.
- It requires few steps for data preparation.
- It is possible to handle numerical and categorical data.
- It is possible to handle multi-output problems.
- It can be used to validate a model using statistical tests.

3.2. Support Vector Machine Classifier

Support vector machines (SVMs) are known as supervised learning models with specific learning algorithms for analysing data in classification and regression. Given several training samples being marked to belong to one of two categories, an SVM training algorithm is then used to build a model for assigning new samples to one category or others. The advantages of support vector machines are:

- They are effective for high dimensional spaces.
- They are still effective when the number of dimensions is greater than the number of samples.
- They can be used with a small subset of training samples in the decision function, so they are very efficient in terms of memory.

3.3. Gaussian Naive Bayes Classifier

Gaussian Naive Bayes (GNB) is a variant of Naive Bayes with Gaussian normal distribution and supports continuous data. Naive Bayes are also a group of supervised machine learning classification algorithms based on the utilisation of Bayes theorem, which is well-known as a simple classification technique but has high functionality. Complicated classification tasks can be performed by using Naive Bayes Classifier.

3.4. k-Nearest Neighbours Classifier

Statistically, the k-nearest neighbours algorithm (k-NN) is also known as a non-parametric supervised learning method for classification and regression. In both circumstances, the input contains the k closest training examples in a data set. The output of the algorithm depends on whether it is used for classification or regression tasks. In classification, the output of k-NN is normally a class membership. An object can be classified based on a majority vote of its neighbours, with the object being assigned to the class most common among its k nearest neighbours (k is typically a small positive integer). If $k = 1$, the object is then assigned to the class of the single nearest neighbour.

3.5. Random Forests Classifier

Random forests are an ensemble learning method, which can be used for classification, regression, and other problems. This operating principle of this learning method is based on constructing a multitude of decision trees at training time. For classification problems, the output of the method is probably the class chosen by most trees. For regression problems, the average prediction of the individual trees can be returned. In general, random forests often outperform decision trees.

3.6. Multi-Layer Perceptron Classifier

Multi-Layer Perception is also known as MLP, which is fully connected dense layers, to transform any input dimension to the desired output dimension. A MLP is a neural network with multiple layers. In an MLP, artificial neurons (nodes) are combined so that the outputs of some neurons become inputs of other neurons. MLPs with a single hidden layer can be sufficient for classification and regression problems. As the number of hidden layers is greater than one, MLP can be known as a type of deep neural networks. The back-propagation technique with the derivative chain is often used to train MLPs.

When using a MLP with finite and noisy DGA data, the regularisation can be used to prevent the parameters of the MLP (weights and biases) from becoming excessively large which can usually cause the overfitting with the unknown test data. This procedure can be carried out with the use of a Bayesian framework applied to the MLP training.

The Bayesian framework can also allow to determine the optimal number of the hidden layer [13]. In the problem of detecting the fault of the power transformer based on DGA, the structure of two nodes in the hidden layer can result in the best performance of the MLP.

4. Power Transformer Fault Classification

In this study, the DGA data for oil-immersed power transformers were directly retrieved from [12]. The DGA data set is in Table 3. An approximate 4 to 1 ratio exists between the number of training samples and the number of test samples. As a result, 190 samples were used to create the training set, and 50 samples were used to create the test set.

Table 3. The DGA data set.

Fault type	Fault code	Number of data samples	
		Training set	Test set
PD	0	21	6
D1	1	33	9
D2	2	44	11
T1	3	56	14
T2	4	14	4
T3	5	22	6
Total number		190	50

Most power transformers only have a few ppm of dissolved gas (part per million). But hundreds or tens of thousands of ppm can be frequently brought on by malfunctioning power transformers. The dissolved gas measurements are typically difficult to see because of this issue. The order of magnitude of DGA concentrations, rather than their absolute levels, can be used to determine the characteristics of DGA data that are the most meaningful. Rescaling DGA data using the logarithmic transform is an efficient technique to account for these changes. In this study, the $\log_{10}$ is utilised for a simple interpretation.

To train the neural network, the data were needed to be normalised to obtain the value between 0 and 1 by using following equation:

$$y_i = \frac{x_i - \min(X)}{\max(X) - \min(X)} \quad (1)$$

Using the ML techniques stated above, the power transformer faults can be categorized. Firstly, the inputs of the ML classifiers must be constructed using the following gas ratios and values:

Doernenburg ratios: The input vector has the following four components:

$$[x] = \begin{bmatrix} \frac{CH_4}{H_2} & \frac{C_2H_2}{C_2H_4} & \frac{C_2H_2}{CH_4} & \frac{C_2H_6}{C_2H_2} \end{bmatrix}^T \quad (2)$$

Rogers ratios: The input vector has the following four components:

$$[x] = \begin{bmatrix} \frac{CH_4}{H_2} & \frac{C_2H_2}{C_2H_4} & \frac{C_2H_4}{C_2H_6} & \frac{C_2H_6}{CH_4} \end{bmatrix}^T \quad (3)$$

IEC ratios: The input vector is based on the following five gas concentrations, each measured in parts per million (ppm):

$$[x] = \begin{bmatrix} \frac{CH_4}{H_2} & \frac{C_2H_2}{C_2H_4} & \frac{C_2H_4}{C_2H_6} \end{bmatrix}^T \quad (4)$$

CSUS: The input vector is based on individual concentrations in parts per million (ppm) of five gases as follows:

$$[x] = [H_2 \quad CH_4 \quad C_2H_4 \quad C_2H_6 \quad C_2H_2]^T \quad (5)$$

For each type of the input vectors, six ML techniques were used to classify the fault kinds of oil-immersed power transformers. The following factors were then used to evaluate how well the prediction model could perform.

Accuracy is used to measure the effectiveness of classification models. Its formal definition is below:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \quad (6)$$

Precision is defined as follows:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (7)$$

where TP and FP stand for the true positive and false positive rates, respectively. The precision can be thought as the classifier's capacity to avoid classifying a negative sample as positive.

Recall is a defined as follows:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (8)$$

where TP and FN stand for the true positive and false negative rates, respectively. The precision can be seen as the classifier's capacity to avoid classifying a positive sample as negative.

F1-Score is defined as follows:

$$\text{F1-Score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (9)$$

The F1-Score can be thought of as a harmonic mean of accuracy and recall, with the highest value being 1 and the poorest being 0.

5. Results and Discussion

The performance metrics for DT, SVC, GNB, k-NN, RF, and MLP classifiers created using Doernenburg ratio-based data are shown in Tables 4, 5, 6, 7, 8, and 9.

Table 4. Performance metrics of the DT classifier formed by using Doernenburg ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	1	1	1
D1	0.82	1	0.9
D2	0.86	0.55	0.67
T1	0.79	0.79	0.79
T2	0.5	0.75	0.6
T3	0.67	0.67	0.67
Accuracy (%)		78	

Table 5. Performance metrics of the SVM classifier formed by using Doernenburg ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	1	1	1
D1	0.67	0.67	0.67
D2	0.75	0.82	0.78
T1	0.77	0.71	0.74
T2	0	0	0
T3	0.71	0.83	0.77
Accuracy (%)		72	

Table 6. Performance metrics of the GNB classifier formed by using Doernenburg ratio-based input data,

Fault Type	Precision	Recall	F1-Score
PD	1	0.83	0.91
D1	0.88	0.78	0.82
D2	0.67	0.73	0.7
T1	0.71	0.71	0.71
T2	0	0	0
T3	0.5	0.67	0.57
Accuracy (%)		68	

Table 7. Performance metrics of the k-NN classifier formed by using Doernenburg ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	0.62	0.83	0.71
D1	0.67	0.89	0.76
D2	0.88	0.64	0.74
T1	0.77	0.71	0.74
T2	0.4	0.5	0.44
T3	1	0.67	0.8
Accuracy (%)		72	

Table 8. Performance metrics of the RF classifier formed by using Doernenburg ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	1	1	1
D1	0.75	1	0.86
D2	1	0.73	0.84
T1	1	0.86	0.92
T2	0.25	0.25	0.25
T3	0.5	0.67	0.57
Accuracy (%)		80	

Table 9. Performance metrics of the MLP classifier formed by using Doernenburg ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	1	1	1
D1	0.8	0.89	0.84
D2	0.82	0.82	0.82
T1	1	0.93	0.96
T2	0.8	1	0.89
T3	1	0.83	0.91
Accuracy (%)		90	

Table 10. Performance metrics of the DT classifier formed by using Rogers ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	0.75	1	0.86
D1	0.89	0.89	0.89
D2	1	0.64	0.78
T1	1	1	1
T2	1	1	1
T3	0.75	1	0.86
Accuracy (%)		90	

The performance metrics for the DT, SVC, GNB, k-NN, RF, and MLP classifiers created using Rogers ratio-based data are shown in Tables 10, 11, 12, 13, 14, and 15.

Table 11. Performance metrics of the SVM classier formed by using Rogers ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	0.86	1	0.92
D1	0.67	0.67	0.67
D2	0.6	0.82	0.69
T1	0.77	0.71	0.74
T2	0.67	0.5	0.57
T3	0.67	0.33	0.44
Accuracy (%)		70	

Table 12. Performance metrics of the NB classifier formed by using Rogers ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	0.33	0.33	0.33
D1	0.55	0.67	0.6
D2	0.71	0.91	0.8
T1	0.83	0.71	0.77
T2	0.75	0.75	0.75
T3	1	0.5	0.67
Accuracy (%)		68	

Table 13. Performance metrics of the k-NN classifier formed by using Rogers ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	0.75	1	0.86
D1	0.67	0.89	0.76
D2	0.73	0.73	0.73
T1	0.83	0.71	0.77
T2	0.5	0.5	0.5
T3	0.67	0.33	0.44
Accuracy (%)		72	

Table 14. Performance metrics of the RF classifier formed by using Rogers ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	1	1	1
D1	0.82	1	0.9
D2	0.88	0.64	0.74
T1	1	0.93	0.96
T2	1	1	1
T3	0.75	1	0.86
Accuracy (%)		90	

Table 15. Performance metrics of the MLP classifier formed by using Rogers ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	1	1	1
D1	0.73	0.89	0.8
D2	0.89	0.73	0.8
T1	1	1	1
T2	1	1	1
T3	1	1	1
Accuracy (%)		92	

The performance metrics of the DT, SVC, GNB, k-NN, RF, and MLP classifiers created utilizing IEC ratio-based data are displayed in Tables 16, 17, 18, 19, 20, and 21.

Table 16. Performance metrics of the DT classifier formed by using IEC ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	0.75	1	0.86
D1	0.89	0.89	0.89
D2	1	0.64	0.78
T1	1	1	1
T2	1	1	1
T3	0.75	1	0.86
Accuracy (%)		90	

Table 17. Performance metrics of the SVM classifier formed by using IEC ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	1	0.83	0.91
D1	0.73	0.89	0.8
D2	0.69	0.82	0.75
T1	1	0.71	0.83
T2	0.75	0.75	0.75
T3	0.71	0.83	0.77
Accuracy (%)		80	

Table 18. Performance metrics of the NB classifier formed by using IEC ratio based-input data.

Fault Type	Precision	Recall	F1-Score
PD	1	0.5	0.67
D1	0.67	0.89	0.76
D2	0.71	0.91	0.8
T1	0.91	0.71	0.8
T2	0.75	0.75	0.75
T3	0.83	0.83	0.83
Accuracy (%)		78	

Table 19. Performance metrics of the k-NN classifier formed by using IEC ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	0.67	1	0.8
D1	0.73	0.89	0.8
D2	0.7	0.64	0.67
T1	0.91	0.71	0.8
T2	0.6	0.75	0.67
T3	1	0.67	0.8
Accuracy (%)		76	

Table 20. Performance metrics of the RF classifier formed by using IEC ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	0.86	1	0.92
D1	0.8	0.89	0.84
D2	0.9	0.82	0.86
T1	1	0.93	0.96
T2	1	1	1
T3	1	1	1
Accuracy (%)		92	

The performance metrics of the DT, SVC, GNB, k-NN, RF, and MLP classifiers created using CSUS-based data are displayed in Tables 22, 23, 24, 25, 26, and 27.

Table 21. Performance metrics of the MLP classifier formed by using IEC ratio-based input data.

Fault Type	Precision	Recall	F1-Score
PD	0.75	1	0.86
D1	0.73	0.89	0.8
D2	1	0.64	0.78
T1	1	1	1
T2	1	0.75	0.86
T3	0.86	1	0.92
Accuracy (%)		88	

Table 22. Performance metrics of the DT classifier formed by using CSUS based-input data.

Fault Type	Precision	Recall	F1-Score
PD	0.75	1	0.86
D1	0.89	0.89	0.89
D2	0.92	1	0.96
T1	0.92	0.86	0.89
T2	0.6	0.75	0.67
T3	1	0.5	0.67
Accuracy (%)		86	

Table 23. Performance metrics of the SVM classifier formed by using CSUS based-input data.

Fault Type	Precision	Recall	F1-Score
PD	0	0	0
D1	0.67	0.22	0.33
D2	0.29	0.45	0.36
T1	0.65	0.93	0.76
T2	0	0	0
T3	0.44	0.67	0.53
Accuracy (%)		48	

Table 24. Performance metrics of the NB classifier formed by using CSUS based-input data.

Fault Type	Precision	Recall	F1-Score
PD	0.67	0.67	0.67
D1	1	0.11	0.2
D2	0.5	0.64	0.56
T1	0.73	0.79	0.76
T2	0.14	0.25	0.18
T3	0.29	0.33	0.31
Accuracy (%)		52	

Table 25. Performance metrics of the k-NN classifier formed by using CSUS based-input data.

Fault Type	Precision	Recall	F1-Score
PD	0.5	0.67	0.57
D1	0.83	0.56	0.67
D2	1	0.55	0.71
T1	0.76	0.93	0.84
T2	0.25	0.25	0.25
T3	0.44	0.67	0.53
Accuracy (%)		66	

When the input vector is created by using the Doernenburg ratios, the GNB classifier results in very low values of precision, recall and F1-Score. The overall accuracy of this classifier is also smaller than that with the remaining methods. Meanwhile, the MLP classifier can give a very accuracy of 90% with acceptable values of precision, recall and F1-score.

Table 26. Performance metrics of the RF classifier formed by using CSUS based-input data.

Fault Type	Precision	Recall	F1-Score
PD	1	1	1
D1	1	1	1
D2	0.92	1	0.96
T1	1	0.86	0.92
T2	0.6	0.75	0.67
T3	0.83	0.83	0.83
Accuracy (%)		92	

Table 27. Performance metrics of the MLP classifier formed by using CSUS based input-data.

Fault Type	Precision	Recall	F1-Score
PD	1	1	1
D1	0.89	0.89	0.89
D2	0.91	0.91	0.91
T1	1	0.93	0.96
T2	0.8	1	0.89
T3	1	1	1
Accuracy (%)		94	

If the Roger ratios are used to form the input vector, the NB classifier probably works ineffectively with quite low values for almost performance metrics including precision, recall, and F1-Score. The DT classifier can give an accuracy of 90% with high values of precision, recall and, F1-score. Especially, the MLP can result in 92% of the accuracy rate. In this case, the MLP and DT classifiers significantly outperform the remaining classifiers.

When the IEC ratios are used to produce the input vector, the DT and RF classifiers have the better performances with the accuracy reaching at 92%. However, the MLP classifier is less effective with an accuracy of 88%.

The use of CSUS to build the input vector can result in very high accuracies of 92% and 94% for the RF and MLP classifiers, respectively. Therefore, this type of the input vector is very appropriate for the MLP classifier.

Table 28 shows a comparison of the six ML classifiers. the DT classifiers can produce the high accuracy rates of power transformer fault classification (equivalent to 90%). Less than 80% of classifications are correctly made using the SVM, NB, and k-NN classifiers. With the accuracy range from 80% to 92%, RF classifiers may provide relatively good accuracy rates without the usage of Doernenburg ratio-based data. Finally, using MLP classifiers can produce results with the maximum accuracy rate of 94%. In general, the RF and MLP classifiers are shown to be superior to other classifiers in terms of effectiveness.

Table 28. Power transformer fault classification accuracies of six ML classifiers with four input criteria.

Classifiers	**Accuracy (%)**			
	Doernenburg Ratios	**Rogers Ratios**	**IEC Ratios**	**CSUS**
DT	78	90	90	86
SVM	72	70	80	48
NB	68	68	78	52
k-NN	72	72	76	66
RF	80	90	92	92
MLP	90	92	88	94

6. Conclusion

This study explores the scikit-learn machine learning tool for Python programming language and outlines critical stages for constructing several sophisticated machine learning classification methods for oil-immersed power transformer problems. To determine the most efficient classifiers for each type of training and test sets, the performances of these classifiers were rigorously assessed and compared. At different schemes of the input vector, the DT, RF and MLP classifier mostly outperform than other types of classifiers. The highest accuracy can be obtained with the MLP classifier. In particular, the use of CSUS to form the invector is very suitable with the MLP classifier. This study has also created a helpful framework for conveniently creating a variety of ML techniques based on scikit-learn for additional categorization issues. The future work for this research is to compare performances of machine learning classifiers deployed by Scikit-learn with machine learning classifiers developed by using Keras and Tensorflow for DGA based power transformer fault diagnosis.

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