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RESEARCH ARTICLE

Investigation of the Effect of Data Preprocessing Methods on the Classifier Performance in Power Transformer Fault Diagnosis

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ABSTRACT

Power transformers are one of the most important and costly equipment of electrical networks. Possible malfunctions that may occur in a power transformer may cause power outages as well as large energy losses. Therefore, it is important to detect the fault in transformers in advance. One of the commonly used methods for fault diagnosis in transformers is to make analyses based on gas concentrations that occur at the time of failure. This method is called dissolved gas analysis (DGA) which is based on measuring gas formation in the transformer insulating fluid during or before the fault. In this study, gas data obtained from DGA was used as the inputs of the chosen machine learning algorithms, and their diagnostic performances were measured. First, the International Electrotechnical Commission Technical Committee (IEC TC)-10 data set which is very popular in the literature was used, and then the real data set obtained from the Turkish Electricity System was applied. Since the data set consists of different sizes, it greatly affects the performance of classification algorithms. Different data preprocessing methods were applied to increase the performance of the algorithms, and how they affect the performance of the algorithms was examined.

Index Terms—Fault diagnosis, power transformer, preprocessing methods

I. INTRODUCTION

Today, with the increasing population, the need for energy is increasing rapidly. As a result of increasing energy need, the fault-free operation of power systems has also gained importance. It is important that the equipment constituting the power system run smoothly in order not to disturb the supply–demand balance and to ensure the electricity transmission smoothly. Power transformers, one of the most important equipment, also come to the fore at this stage [1, 2]. In case of a possible failure in power transformers, the system will be adversely affected, and hence fault diagnosis has become important and also has become one of the most significant research topics.

Different methods are applied for fault diagnosis in power transformers. One of them is to diagnose faults by interpreting the gas concentrations formed in the insulating liquid. First of all, it is necessary to determine the gas concentrations formed in the transformer insulating liquid. For this, the dissolved gas analysis (DGA) method is used, and the gas concentrations that occur in the transformer insulation fluid before or in the event of a failure are determined. Since these gas concentrations have different formation temperatures and energies, they are used as a guide in fault diagnosis.

Gas concentrations obtained from DGA are used with different interpretation methods, and fault diagnosis is made. Classical methods, which have been widely used in the literature for many years, diagnose faults based on experience and rule bases based on old data. Examples of classical interpretation methods in the literature are Roger gas ratio method [3], Doernenburg gas ratio method [3], IEC gas ratio method [4], Duval triangle method [3], and Duval pentagon method. Since the rule bases created in these methods do not contain some fault conditions or do not comply with the created rule base, exact fault diagnosis cannot be made. Therefore, the use of smart methods has begun to reduce these deficiencies and increase the diagnostic capability. Some of the intelligent methods are expert systems, fuzzy methods, artificial intelligence-based methods, and machine learning methods.

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In 2018, Senoussaoui et al. [5], artificial intelligence methods Bayes Network (Bayes Network) and multilayer perceptron neural network (MLPNN) methods, as well as machine learning methods K-nearest neighbor (KNN) algorithm and decision tree (DT) algorithms and compared their fault diagnosis performance. In 2019, Chatterjee et al. [6], using combinations of different gas ratios, performed transformer fault diagnosis with fuzzy logic and MLPNN algorithm and obtained successful results. In 2020, Shahrabad et al. [7], using gas data, diagnosed the support vector machine (SVM) and DT algorithms and showed that the DT algorithm provides better diagnostics for the data set they use. In 2021, Kherif et al. [8] performed fault diagnosis with the KNN algorithm using the DT rule base using different input vectors they created from the gas data. In 2021, Wu et al. [9] used 300 gas data in their study and used Kernel principal component analysis for feature extraction from these gas data. They used the improved seagull optimization algorithm for parameter optimization to eliminate the deficiencies of SVM-based fault diagnosis and compared the obtained results with other optimization algorithms [9]. In 2022, Ekojono et al. [10] added different features to the data set using different Duval methods. Then, using the data set they created, they made a diagnosis with DT, random forest (RF), naive Bayes, and artificial neural networks. In 2022, Wu et al. [9] applied normalization to the data to make the data set ready. They proposed the improved grey wolf optimization algorithm to overcome the low population diversity and early and slow convergence problems of the grey wolf optimization algorithm. They used the least square SVM to reduce the complexity of the diagnostic model and increase the diagnostic accuracy [11]. In 2022, Mao et al. [12] proposed the multivariate time-series graph neural network algorithm because of the poor diagnostic performance of traditional methods and the neglect of the time dimension in supply diagnostics. The graphical structure shows the relationship between gases, and abnormal situations can be detected beforehand with the help of the weights in the graph. It was stated that this method would be a guide for the maintenance personnel and they compared it with the classical methods [12]. In 2023, Li and Xiao [13] used 565 DGA data. Since the grasshopper optimization algorithm tends to decrease to the local optimum, they defined the sigmoid function and used the improved grasshopper optimization algorithm algorithm for the optimization of the SVM parameters. [13]. In 2023, Hechifa et al. [14] used gas ratios and percentages in classical methods to increase the number of features in the data set. For fault diagnosis, classification algorithms RF, tree ensemble, gradient boosted tree, and extreme gradient tree algorithms were used, and their results were compared [14]. In 2023, Demirci et al. [15] performed transformer fault diagnosis with different machine learning algorithms and Kalman filter fusion algorithm using log transformed + standardized gas data.

Main Points

- Support vector machine, K-nearest neighbor, decision tree, and multilayer perceptron neural network algorithms are used for transformer fault diagnosis.
- Different preprocessing steps have been applied to improve the performance of classification algorithms.
- Analyses have been first made with the IEC TC-10 data set taken from the literature, and then the processes have been repeated with the real data set.
- The effects of preprocessing steps on the classifier performance have been compared.

In this study, different data preprocessing methods are applied to the data set to be used first. In artificial intelligence-based methods and machine learning methods, the data set is used in the training and testing of the algorithm in the classification process. Different data preprocessing methods are used to prepare the used data set for classification algorithms. The data preprocessing methods used in this study are gas percentage transformation [16], logarithmic transformation [15], normalization [17], standardization [15], arctangent transform [18], and logarithmic transformation + standardization [15]. Then, the SVM, KNN, and DT algorithms, which are widely used in recent years, and the MLPNN algorithm from artificial neural networks have been used in transformer fault diagnosis. In addition, transformers have been classified in four different states as normal situation, partial discharge, arc faults, and thermal faults, and fault diagnosis has been made according to these cases. Diagnostic results of different preprocessing methods have been obtained, and the results have been compared to each other.

This paper was organized as follows: In first part, a summary of the DGA method is given and the classification algorithms used are explained. In the second part, data preprocessing methods and the equations of the methods are also given. Then, the data set used for the diagnostic process and the diagnostic results of the different situations created for the diagnosis are presented. In the final part, the obtained results are explained and evaluated.

A. Dissolved Gas Analysis

In case of any failure in power transformers, gases with different formation temperatures and energies begin to form in the insulating oil. Dissolved gas analysis measures these gas concentrations formed in the insulating oil in power transformers with different methods. Gases are formed in the insulating oil in case of failure and can be measured. These gases are hydrogen, methane, ethane, ethylene, acetylene, nitrogen, carbon dioxide, carbon monoxide, and oxygen. Among these gases, hydrogen, methane, ethane, acetylene, and ethylene are called characteristic gases. These characteristic gases formed in the insulation oil in case of failure or before any failure inform the user about the failure, and measures can be taken before the failure becomes irreparable [3, 4].

B. Classification Algorithms

In the present study, intelligent methods are used for fault diagnosis. These methods have been used to overcome the shortcomings of conventional methods and to increase the diagnostic capability. The classification algorithms used are SVM, DT, KNN, and MLPNN methods, and different data preprocessing methods are used to increase the performance of these methods.

- Support vector machine has been preferred due to its high generalization ability and high accuracy performance. Support vector machine is frequently used in classification and regression problems, and it performs these operations by determining a hyperplane between the data. It produces solutions to problems by adjusting the margin between a determined optimal hyperplane and the data to be maximum [15, 19].

- K-nearest neighbor has been preferred due to its ease of application and easy-to-understand structure. In the KNN algorithm, the distance of the data to be classified from the labeled data is measured, then the number of neighbors is determined, the labels of the nearest neighbors are determined, and finally the unlabeled data is labeled with the highest number of neighbor labels [20].
- Decision tree is the preferred algorithm because of its simplicity in computational complexity and high classification accuracy. In the classification process, the attributes in the data set are used, and a series of questions are asked according to these attributes and the result is reached according to the answers received. Using the DT algorithm in transformer diagnostics makes it easier for operation and maintenance personnel to obtain rules to use to evaluate transformer condition. By following the step-by-step conditions and outputs, the personnel can also reach a diagnosis. Transformer condition evaluation rules can be created regionally when the knowledge obtained from the DT algorithm is combined with the experience of the experts [21, 22].
- Multilayer perceptron neural network, on the other hand, is preferred due to its ease of implementation, fast operation, and ability to work with a small number of data. The architecture of MLP consists of an input layer, a variable number of hidden layers, and an output layer. The number of hidden layers in the MLPNN structure and the number of neurons in the hidden layer vary according to the application used and are determined by experiment [23]. In MLPNN used in classification processes, the number of neurons in the input layer is equal to the number of features in the data set, while the number of neurons in the output layer is as much as the number of class labels.

II. DATA PREPROCESSING METHODS

In power transformers, the gas concentrations used in fault diagnosis are at very different values in normal and faulty conditions. The fact that the gas concentrations are in very different values is convenient for the application of statistical learning algorithms. Therefore, before the classification process, the data are preprocessed. The data preprocessing methods used in this study are logarithmic transform, gas percentages, normalization, standardization and logarithmic transformation + standardization, and arctangent transform. Equations of these are given in Table I.

TABLE I.
EQUATIONS OF PREPROCESSING METHODS

Preprocessing Methods	Equations
Gas percentage transform	$X = X_i / (TDCG)$ $\mathrm{TDCG} = H_2 + CH_4 + C_2H_6 + C_2H_4 + C_2H_2$
Logarithmic transform	$X = \log(X_i)$ $\log(X_i)$= logarithmic value of X_i
Normalization	$X = \frac{X_i - \min(X_i)}{\max(X_i) - \min(X_i)}$. *min* ($X_i$)= minimum value of X_i *max* (X_i)=maximum value of X_i
Standardization	$X = \frac{Xi - \mathrm{mean}(X_i)}{\mathrm{Std}(X_i)}$ *mean* (X_i)= mean value of X_i *Std* (X_i)= standardization of X_i
Log transform + standardization	$Xii = \log(X_i)$ $X = (X_{ii} - \mathrm{mean}(X_{ii}))/(\mathrm{Std}(X_{ii}))$
Arctangent transform	$X = \mathrm{arctangent}(X_i)$

X, processed data; X_i, gas concentration.

III. FAULT DIAGNOSIS

A. Data Set

In the present work, which examines the effect of data preprocessing step on fault diagnosis in power transformers, first the IEC TC-10 data set, which is widely used in the literature, has been used [24]. This data set consists of 167 data including five characteristic gas concentrations and four different transformer states. In the data set, partial discharge faults are 5.38%, arc faults are 29.94%, thermal faults are 20.35%, and normal state data is 44.31%.

Then, the real gas data obtained from the transformers used in the Turkish Electricity System have been used, and the effects of data preprocessing methods on the diagnostic performance are compared. The actual data set contains 355 gas data and includes four transformer states. The data set content is as follows: 6% PD, 26.5% arc fault, 44.2 % thermal fault, and 23.3% normal condition.

IV. FAULT DIAGNOSIS RESULTS

Six different case studies have created using the raw data set and the processed data sets and transformer fault diagnostic process has performed with classification algorithms with these data. Cross validation (CV) has been used in the classification process. In the CV process, the data set is divided into the specified number, and while one of the parts is used as a test data set, the others are used as a training data set. This process is repeated until all parts have test data. Here, CV = 5, and the data set have been divided into five parts and fault test results have been obtained. In the first stage, IEC TC-10 data set has been used as data set 1, and in the second stage, real data set has been used as data set 2. The effects of different preprocessing steps applied to the data on the distribution of the data are shown in Fig. 2 and the diagnostic results.

A. Data set 1

Case 1: The data that have not been subjected to any preprocessing are used as the data set and diagnostic results are obtained from the classification algorithms. In the classification process made with raw data sets, the highest diagnostic performance has obtained in the KNN algorithm with 77.21%.

Case 2: The data set has been created by taking gas percentages. The performance of all classifiers increased in the classification process made with the data set using gas percentages. The highest diagnostic performance has obtained in the MLPNN algorithm with 85.04%.

Case 3: Logarithmic transform operations have been applied successfully. In the classification process where logarithmic transformed data is used, the highest diagnostic accuracy belongs to the KNN algorithm with 83.22%.

Case 4: Normalization process has been applied to the data, and fault detection operations have been performed with these data. Contrary to the SVM algorithm in normalized data, KNN and MLPNN algorithms have showed higher performance than raw data.

Case 5: Standardization process has been applied to the data. In the diagnostic process using standardized data, the diagnostic performance of the SVM algorithm has decreased in contrast to other algorithms.

Case 6: Logarithmic transformation + standardization process has been applied to the data set, and fault diagnosis results have obtained with classifiers. In the classification process using data where logarithmic transformation + standardization process has been applied, the diagnostic performance for all classifiers increased compared to the classification process made with raw data. The highest diagnostic performance was obtained with the KNN algorithm with 84.42%. The highest diagnostic performance was obtained with the KNN algorithm at 84.42%.

Case 7: Arctangent transform process is applied to the data set, and fault diagnosis results are obtained with classifiers. The results show that arctangent conversion, which is used in the literature, is not a suitable data conversion method for the IEC TC-10 data set used in transformer fault diagnosis.

The classifier results of all data preprocessing methods applied to the IEC TC-10 data set are given in Table II.

The classifier performances of different data preprocessing methods using the IEC TC-10 data set are given in Fig. 1. The highest diagnostic accuracy has been achieved with the log transform + standardization process in Case 6. The distribution of the raw data set and the distribution of the log transform + standardized data are given in Fig. 2 to show how the data preprocessing method affects the distribution of the data set.

When the scatter plot of the raw data set in Fig. 2 is examined, it is seen that all the data are located in a wide range, but there is an accumulation in a certain range. The purpose of data preprocessing is to avoid this clutter and better prepare the data for classification algorithms. When we look at the scatter graph of the log transform + standardized data, it is seen that the distribution of the data set is limited and not stacked in a certain area.

B. Data Set 2

All of the preprocessing methods were applied as the first step to the real data set one by one, and diagnostic accuracy has been obtained

TABLE II.
FAULT DIAGNOSIS ACCURACIES OF ALL CASES OF IEC TC-10 DATA SET

	Fault Diagnosis Accuracy (%)			
Case No.	**SVM**	**KNN**	**DT**	**MLPNN**
Case 1: raw data	73.67	77.21	75.43	44.02
Case 2: gas percentage data	82.08	83.83	79.09	85.04
Case 3: log-transformed data	80.87	83.22	74.83	80.89
Case 4: normalized data	46.07	79.05	75.43	53.88
Case 5: standardized data	55.72	79.64	75.43	73.11
Case 6: log-transformed + standardized data	82.01	84.42	73.67	82.04
Case 7: Arctangent-transformed data	59.3	76.07	74.79	59.91

DT, decision tree; KNN, K-nearest neighbor; MLPNN, multilayer perceptron neural network; SVM, support vector machine.

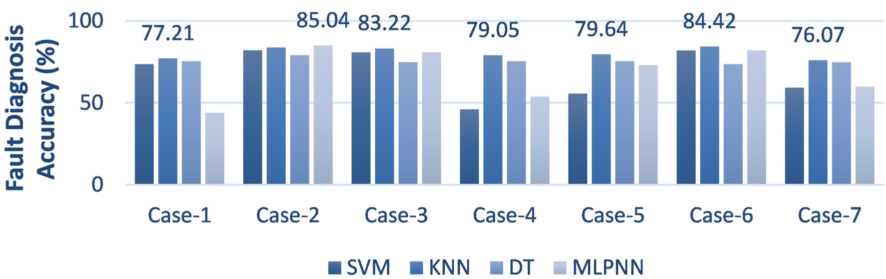

Fig. 1. Fault diagnosis accuracies of the IEC TC-10 data set.

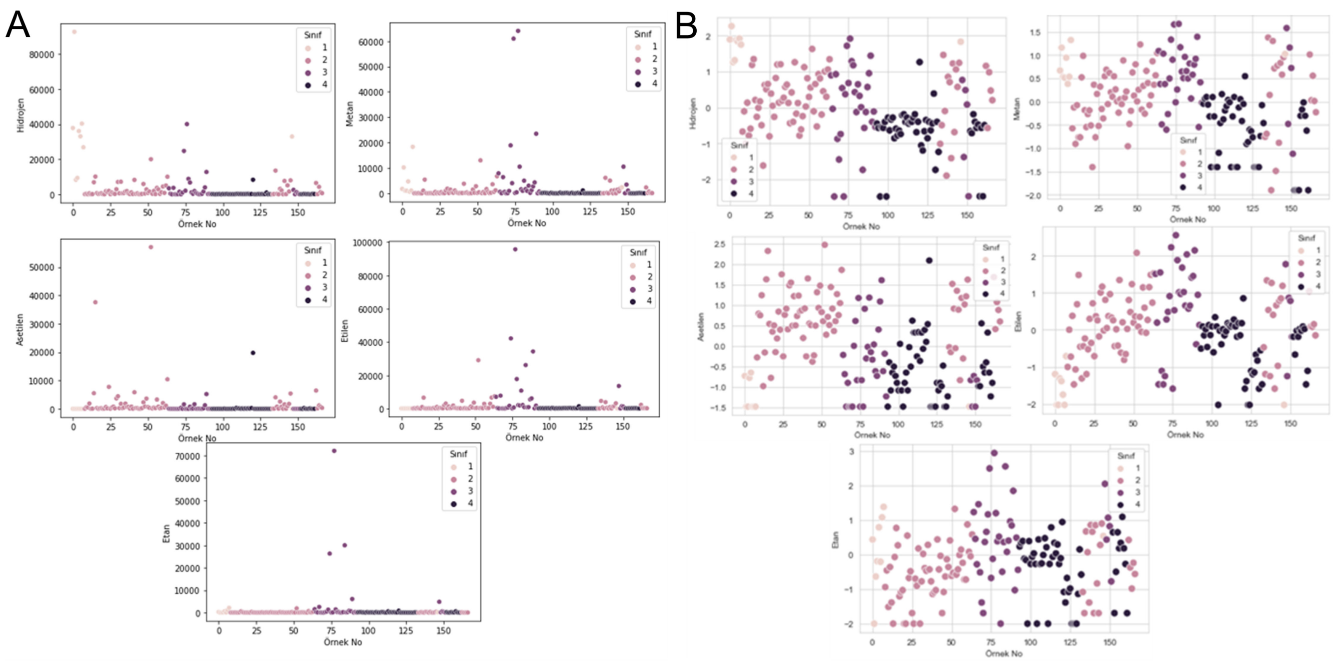

Fig. 2. Scatter plot of the IEC TC-10 data Set: (a) raw data and (b) log transform + standardized data.

from the classification algorithms. Fault diagnosis accuracies for each case are given in Table III.

The results of the raw data set and processed data have compared. It has been observed that some data preprocessing methods increase the diagnostic accuracy, while others decrease it.

TABLE III
FAULT DIAGNOSIS ACCURACY OF REAL GAS DATA

	Fault Diagnosis Accuracy (%)			
Case No.	**SVM**	**KNN**	**DT**	**MLPNN**
Case 1: raw data	69	72.1	73.2	69.01
Case 2: gas percentage data	68.7	72.7	70.1	65.35
Case 3: log-transformed data	75.8	80.8	72.4	70.98
Case 4: normalized data	65.6	71.3	71.8	45.02
Case-5: Standardized Data	67.3	72.1	71.8	58.2
Case 6: log-transformed + standardized data	81.9	78.6	76.1	76.05
Case 7: arctangent-transformed data	74.1	75.8	74.9	59.6

DT, decision tree; KNN, K-nearest neighbor; MLPNN, multilayer perceptron neural network; SVM, support vector machine.

The highest diagnostic accuracy obtained using the raw data set belongs to the DT algorithm with 73.2%. The confusion matrix of DT is given in Fig. 3.

When the diagnostic accuracies obtained using preprocessing methods are compared, the highest diagnostic accuracy has been obtained with SVM in case 6, and the confusion matrix of this method is given

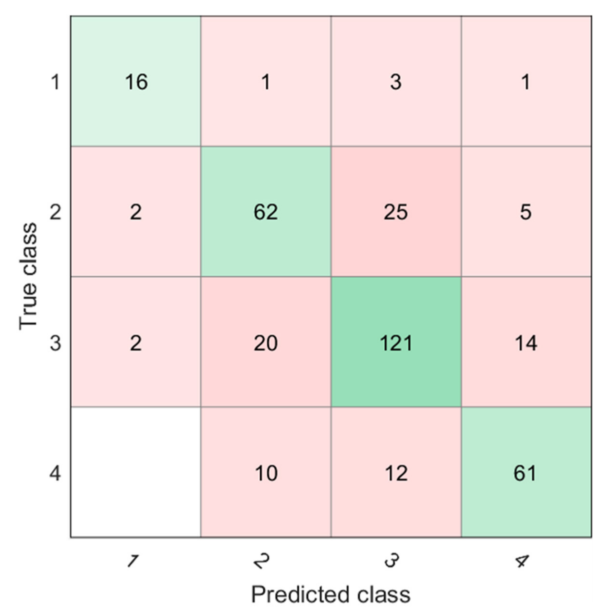

Fig. 3. Confusion matrix of decision tree in case 1.

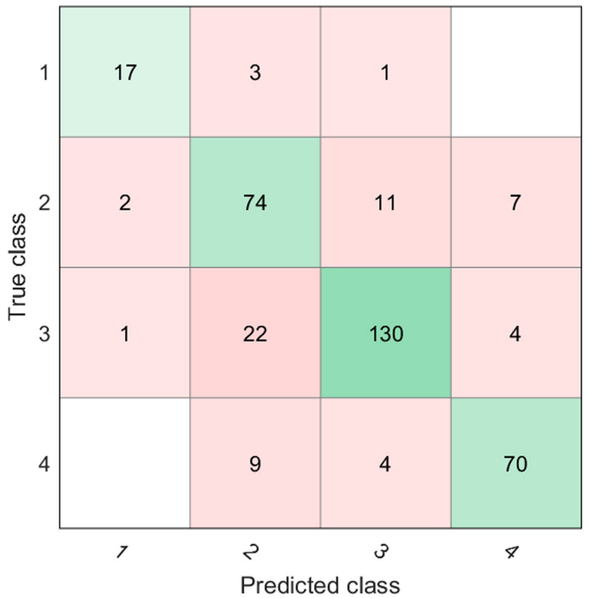

Fig. 4. Confusion matrix of SVM in case 6. SVM, support vector machine.

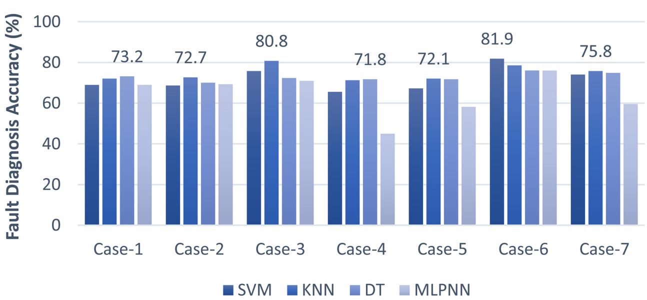

Fig. 5. Fault diagnosis accuracies of the real data set.

in Fig. 4. The classifier performances of different data preprocessing methods using the IEC TC-10 data set are also given in Fig. 5.

V. CONCLUSION

In the present study,

- For transformer fault diagnosis, first the IEC TC-10 data set and then the real gas data from the Turkey Electricity System are used.
- Support vector machine, DT, KNN, and MLPNN classification algorithms are used for fault diagnosis.
- Different data preprocessing methods are used to observe the effects of the used data set on the diagnostic performance of the classifier algorithms.
- The data preprocessing methods used are gas percentage conversion, logarithmic transformation, normalization, standardization, log transform + standardization, and arctangent transform.
- The raw data and the data obtained by these data preprocessing methods are used as the input data for each classifier, and diagnostic performances are obtained.

For the IEC TC-10 data set,

- The highest accuracy is obtained from the KNN algorithm, with 77.21%, in the diagnostic process with the raw data set. When gas percentage conversion, one of the data preprocessing methods, is used, the highest diagnostic accuracy is obtained from the MLPNN algorithm with 85.04%.

For a real data set,

- The highest accuracy is obtained from the DT algorithm, with 73.2%, in the diagnostic process with the raw data set. In the faultdiagnosis process made with data subjected to log transformation + standardization process, which is one of the data preprocessing methods, the highest diagnosis accuracy is obtained from the SVM algorithm with 81.9%.

Finally, the results obtained from the analyses showed that the effectiveness of data preprocessing methods differs according to the data set used. In addition, it is observed that the fault diagnostic performance increases when the data preprocessing method is selected according to the used classifier algorithm. In this study, different preprocessing methods applied in the literature are presented, and the effects of these methods on fault diagnosis performance for different classification algorithms has been presented comparatively.

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