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Identification of Transformer Anomalies Utilizing the AdaBoost Machine Learning Algorithm

Identifikasi Anomali Transformator Menggunakan Algoritma Machine Learning AdaBoost

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Abstract – Electrical energy is one of the most important needs in the local area, concerning the provision of electrical power a transformer is needed to distribute electrical power to each house. The use of transformers in each area requires testing the oil content in them to assess the state of the transformer. The Duval Pentagon Method (DPM) and the Duval Triangle Method (DTM) can be used in tests to identify transformer interference. Owing to the vast quantity of transformers utilized in public energy distribution, the Adaboost machine learning method was applied to identify transformer disruptions. By categorizing test data on a dataset derived from tests conducted with the earlier DTM and DPM techniques, the AdaBoost algorithm predicts transformer disruptions. According to the findings of tests conducted using the best dataset, the division used 80% of the data for training and reserved 20% for testing, using a learning rate of 1 and an estimator of 400 for DTM. This resulted in an accuracy level of 91.1%, which is an excellent classification. In contrast, the DPM approach divides the dataset into 80% training and 20% testing, employs an estimator of 500, and has a learning rate of 0.5. This leads to an excellent classification accuracy rate of 84.9%.

Keywords: Adaboost, Duval Pentagon Method, Transformer, Duval Triangle Method

Abstrak- *Energi listrik merupakan salah satu kebutuhan terpenting di daerah, dalam hal penyediaan daya listrik diperlukan sebuah transformator untuk menyalurkan daya listrik ke setiap rumah. Penggunaan transformator di setiap daerah memerlukan pengujian kandungan minyak di dalamnya untuk menilai keadaan transformator. Metode Duval Pentagon (DPM) dan Metode Duval Triangle (DTM) dapat digunakan dalam pengujian untuk mengidentifikasi gangguan transformator. Karena banyaknya transformator yang digunakan dalam distribusi energi publik, metode machine learning Adaboost diterapkan untuk mengidentifikasi gangguan transformator dengan mengkategorikan data uji pada dataset yang berasal dari pengujian yang dilakukan dengan teknik DTM dan DPM sebelumnya dan algoritma AdaBoost memprediksi gangguan transformator. Di dalam pengujian yang dilakukan dengan menggunakan dataset yang terbaik untuk divisi tersebut menggunakan 80% data untuk data training dan 20% untuk pengujian, menggunakan laju pembelajaran 1 dan estimator 400 untuk DTM. Ini menghasilkan tingkat akurasi 91,1%, yang merupakan klasifikasi yang sangat baik. Sebaliknya, pendekatan DPM membagi kumpulan data menjadi 80% pelatihan dan 20% pengujian, menggunakan estimator 500, dan memiliki tingkat pembelajaran 0,5. Hal ini menghasilkan tingkat akurasi klasifikasi yang sangat baik sebesar 84,9%.*

Kata kunci: *Adaboost, Duval Pentagon Method, Transformer, Duval Triangle Method*

INTRODUCTION

The efficient distribution of electric power is crucial for the functionality of various systems, with transformers playing a pivotal role in this process. Transformers serve as essential equipment, facilitating the distribution of electric power and enabling the transformation of voltage levels from high to medium and vice versa. Notably, transformers contain oil, functioning as both a coolant and an insulator, which harbors dissolved gases. The presence of these gases can lead to transformer failures (Y.Afrida, 2022).

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Comprehensive condition analysis is very important in overcoming the challenge of minimal transformer failure. Dissolved Gas Analysis (DGA) has emerged globally as a method for detecting potential faults in transformers (N.A Bakar, 2017). DGA specifically monitors gases such as H2, CH4, CO, CO2, C2H4, C2H6, C2H2, O2, N2, and O2N2, which are often challenging to detect through conventional characteristic testing. However, interpreting DGA results poses a challenge due to the inherent nature of error-prone outcomes. Enhance the interpretability of DGA results, this study employs the Duval Triangle Method (DTM) and the Duval Pentagon Method (DPM) (N. Pattanadech and W. Wattakapaiboon, 2019).

Pursuing enhanced outcomes, a development of an application that employs the AdaBoost machine learning algorithm is undertaken to identify disturbances in transformers utilized in electricity distribution. The proposed study aims to contribute to the classification of transformer damage through the application of the AdaBoost machine learning algorithm. AdaBoost, a widely recognized algorithm, plays a pivotal role in assessing the performance of machine learning systems. Accuracy, in this context, is defined as the degree of correlation between forecasted values and real values.

The application of the AdaBoost algorithm, combined with the DTM and DPM methods, enhances the accuracy of transformer fault identification. AdaBoost is an ensemble learning technique designed to improve classification accuracy, especially in cases where datasets have imbalanced classes. The algorithm starts by initializing weights for all training samples equally. It then iteratively trains weak classifiers (typically decision trees) by increasing the weights of misclassified samples, thus focusing on more challenging cases in subsequent rounds. The final model is a weighted combination of these classifiers, which improves overall prediction accuracy through a voting mechanism that prioritizes classifiers with better performance (Freund & Schapire, 1997).

The AdaBoost machine learning algorithm is employed in this study to identify faults in transformers based on dissolved gas analysis in transformer oil. However, it is essential to acknowledge the limitations of the proposed approach. The application is designed exclusively for identifying faults using DTM and DPM. Additionally, the study does not delve into strategies for improving conditions in transformers experiencing gas failures. Previous research in this domain has explored the identification of transformer faults using various machine learning techniques, including Neural Network (NN) resulting in an accuracy of almost 90% (V. Rokani, 2023), Decision Tree (DT), Random Forest (RF), Support Vector Method (SVM), Naïve Bayes (NB), and Adaptive Boosting (AB) in conjunction with the DPM. Notably, a previous study achieved an impressive accuracy level of 96.5%. This current study aims to advance the field by combining the DTM and DPM, presenting accuracy comparisons of 75% for DTM and 88% for DPM.

The paper is organized as follows. First, the introduction provides an overview of the research objectives and the significance of advancing fault diagnosis methodologies. Following this, the methodology section outlines the steps involved in implementing the DPM and conducting fault analysis. The results section presents the findings of the fault diagnosis process, including the categorization of fault types and their implications. In the discussion section, the real-world impact of the research is discussed, along with comparisons with studies in other fields and potential avenues for future research. Finally, the conclusion summarizes the key findings and highlights the importance of the research contributions.

Prasojo et al. (2023) Precise transformer fault diagnosis via random forest model enhanced by synthetic minority over-sampling technique the researchers identify transformer faults using the Duval Pentagon Method (DPM) combined with several machine learning algorithms: K-Nearest Neighbor (KNN), Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), Neural Network (NN), Naïve Bayes (NB), and Adaptive Boosting (AB). They achieved an accuracy rate of 96.5%.

Duval and Lamarre (2014), in their study titled "Application of Duval Pentagon Compared with Other DGA Interpretation Techniques: Case Studies for Actual Transformer Inspections Including Experience from Power Plants in Thailand," combined Duval Triangle Method (DTM) and Duval Pentagon Method (DPM) to identify transformer faults, achieving accuracies of 75% for DTM and 88% for DPM. Additionally, Rohman et al. (2017) in their article titled "Application of C4.5 Algorithm Based on Adaboost for Heart Disease Prediction" concluded that using the C4.5 algorithm based on Adaboost achieved an accuracy of 92.24% for predicting heart disease, which was better than using only the C4.5 algorithm. These studies demonstrate the effectiveness of combining advanced machine learning techniques with established methods like the Duval Pentagon Method for precise fault diagnosis in transformers and disease prediction.

RESEARCH METHOD

The research method to be applied in developing the application for identifying transformer faults is the Software Development Life Cycle (SDLC) Model Waterfall.

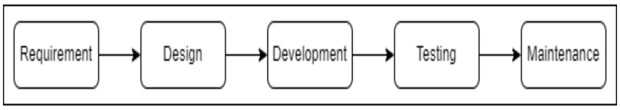

Figure 1 SDLC Waterfall

1. Requirement Analysis
   In this stage, the system requirements analysis is conducted for the software and hardware to be used, as well as functional and non-functional requirements.
2. Design
   The design phase involves system design including system architecture, flowcharts, use case diagrams, activity diagrams, and sequence diagrams that will be developed for the transformer fault identification application.
3. Development
   Based on the designs from the previous stage, this phase involves implementing them into program code. The application will be developed using the PySimpleGUI approach in Python programming language, utilizing a MySQL database, and integrating the DTM and DPM in the AdaBoost machine learning algorithm.
4. Testing
   During the testing phase, the developed system will be tested to ensure that it meets the specified requirements. The goal is to assess the success of the AdaBoost machine learning algorithm in applying the DTM and DPM methods to identify conditions and failures in transformers.

The issue at hand is that there are a large number of transformers used in distributing electricity to the public. Each transformer requires periodic condition checks to assess its health status. This is crucial because if transformer faults are not identified promptly, they can lead to severe damage or even explosions. These checks involve testing the concentration of dissolved gases in transformer oil. The required gas concentrations for testing can vary depending on the method used. For the DTM, the required gas concentrations are CH_4, C_2H_2, and C_2H_4. Meanwhile, for the DPM, the required gases are H_2, CH_4, C_2H_2, C_2H_4, and C_2H_6.

Determine the point of failure using these methods, calculations are required. This process can be time-consuming, especially when testing numerous transformers, as testers need to perform calculations for each transformer with different dissolved gas concentrations. Therefore, the development of this application aims to expedite and to simplify the process of identifying faults in transformers.

The DGA testing method is divided into two, namely the characteristic gas limit and the ratio method. The characteristic method is used to derive the characteristics of the gas during operation. Meanwhile, the ratio method serves as a measure of accuracy in identifying damaged and normal components to reduce the object of analysis (Y.Yue, 2021). The outcomes of the DGA (Dissolved Gas Analysis) test are presented as gas components, including hydrogen (H_2), methane (CH_4), carbon monoxide (CO), carbon dioxide (CO_2), acetylene (C_2H_2), ethane (C_2H_6), and ethene (C_2H_4). These gas levels tend to escalate as the transformer temperature increases. The elevation in transformer temperature accelerates the reaction of hydrocarbons in the oil, particularly the formation of ethane and ethylene gases, which are commonly associated with elevated temperatures caused by hot metals [8]. Several steps that need to be carried out are sampling, gas extraction from oil, gas analysis for evacuating and concluding.

In 1974, Michel Duval introduced this approach for analyzing the dissolved gas generated by a transformer. It involves inputting a set of hydrocarbons, specifically methane (CH_4), ethylene (C_2H_4), and acetylene (C_2H_2), which are positioned at the vertices of an equilateral triangle, symbolizing the relative gas proportions (A.Gupta,2019). The following illustrates the use of the DTM method in determining the area of failure of a transformer in the figure 2.

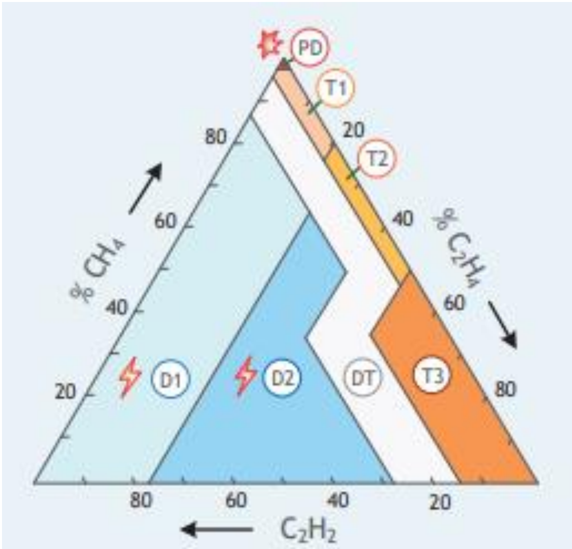

Figure 2 Duval Triangle Method

From Figure 2 , it can be concluded that the results of the DTM with 3 inputs are as in Figure 3 below:

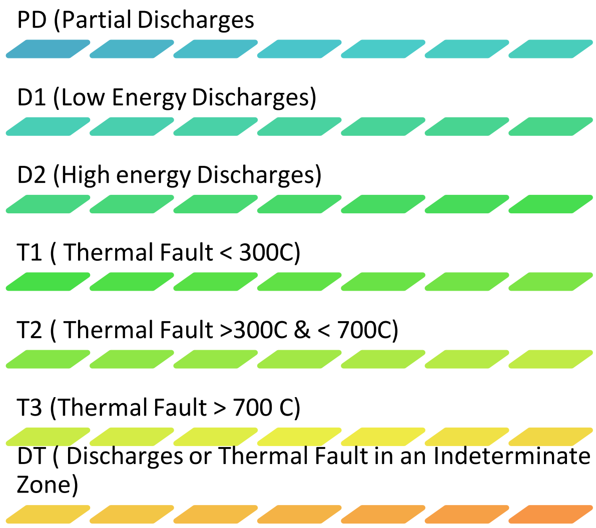

Figure 3 Lists the Fault Categories in the Duval Triangle Method (DTM)

Figure 3 illustrates a comprehensive depiction of Fault Categories within the DTM) The Duval Triangle Method is a structured approach used for fault analysis and categorization.

The DPM helps determine gases that cannot be identified in the DTM, namely hydrogen gas (H2) and ethane (C2H6). To find out the damage point in a transformer using the DPM method, it is necessary to carry out calculations in several stages as follows:

Calculate the relative percentage of dissolved gas with the formula:

$$\frac{(Dissolved\ gas\ content)}{(Total\ dissolved\ gas\ content)}\ x\ 100\% \qquad (1)$$

a) Calculating the point (x, y) of each dissolved gas with the formula:

$$\frac{(Relative\ percentage\ of\ dissolved\ gas)}{100}\ x\ Cos \propto \qquad (2)$$

Each dissolved gas has an alpha angle of H2 = 90, CH4 = 234, C2H2 = 18, C2H4 = 306, and C2H6 = 162 so that the results of cos alpha H2 = (0, 100), CH4 = (-58.8, - 80.9), C2H2= (95.1, 30.9), C2H4= (58.8, -80.9), and C2H6= (-95.1, 30.9) (M.Duval, 2014)

b) Calculating the polygon surface with the formula below:

$$A = \frac{1}{2}\sum_{i-0}^{n-1}(x_i y_{i+1} - x_{i+1} y_i) \qquad (3)$$

Notes:

A = Point surface of the polygon

i = Order of coordinate points

n = Total points

c) Calculating Cx and Cy points using the following two formulas:

$$C_x = \frac{1}{6A}\sum_{i-0}^{n-1}(x_i + x_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \quad (4)$$

$$C_y = \frac{1}{6A}\sum_{i-0}^{n-1}(y_i + y_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \quad (5)$$

The results of these calculations are in the form of Cx and Cy points which indicate the point of damage to the transformer being tested. The type of failure or condition on the transformer from the calculation results can be seen in Figure 4:

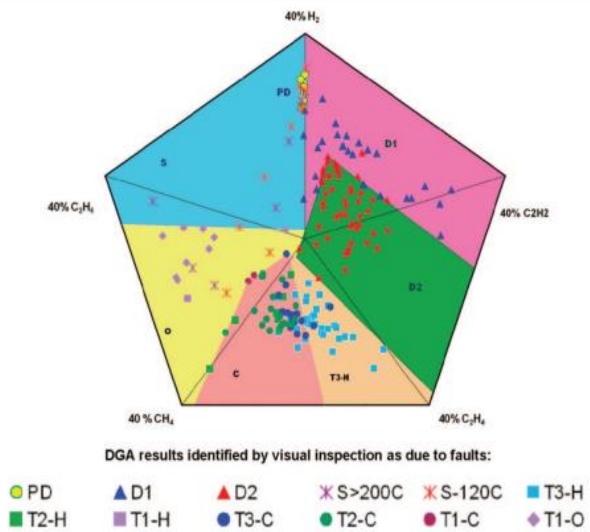

Figure 4 Duval Pentagon Method

From Figure 4 , it can be concluded that the results of DPM with 5 inputs are as in Figure 5 below Figure 5 provides a detailed depiction outlining the Fault Categories within the DPM. The DPM is a systematic approach employed for fault analysis and categorization, and this visual representation serves to elucidate the various fault categories integrated into the methodology.

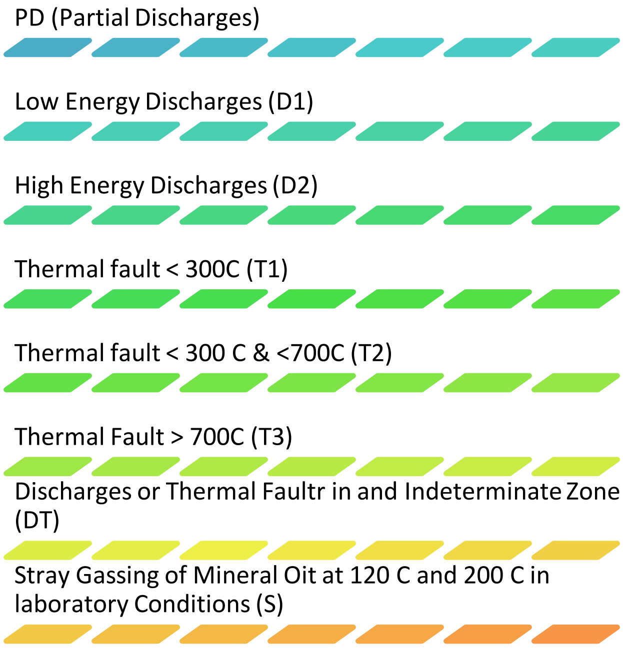

Figure 5 Outlines the Fault Categories in the DPM

Partial Discharges (PD) are localized electrical discharges within high-voltage equipment insulation, and categorizing them is crucial for equipment health assessment. Within this framework, Low Energy Discharges (D1) represent PD events with relatively low energy levels, providing insight into the insulation's condition. On the other hand, High Energy Discharges (D2) signify more intense PD occurrences, signaling potential severe issues. Thermal faults are also categorized into three groups: Thermal fault < 300°C (T1), Thermal fault < 300°C & <700°C (T2), and Thermal Fault > 700°C (T3), each denoting different temperature ranges and associated risks. Discharges or Thermal Faults falling into an Indeterminate Zone (DT) require careful analysis due to ambiguity. Additionally, Stray Gassing of Mineral Oil at 120°C and 200°C in laboratory conditions (S) is considered, adding an extra dimension to the assessment of potential faults. This categorization system aids in systematically evaluating and addressing various Partial Discharge scenarios for effective maintenance and reliability of high-voltage equipment.

The Adaptive Boosting (AdaBoost) method is a method used to identify difficult minority classes but still maintains the ability to classify the minority class more effectively and has a high identification rate. This method is proposed with selective costing to make it more effective, applying an ensemble learning method that can reduce the variance of a classification set.

The stages in the AdaBoost method are as follows:

a) Initialize the data weights $\{W_n\}$ with $W_n^{(m)}$ for n = 1, 2, 3, …., N. n is the number of models and N is the individual models known as the decision tree.

b) For m = 1……, M. m is the number of weighted records.

i. Training $y_m(x)$ by minimizing the error function.

$$J_m = \sum_{n=1}^{N} W_n^{(m)}{}_n I\,(y_m(x_n) \neq t_n \quad (6)$$

ii. Error evaluation

$$\varepsilon_m = \frac{\sum_n^N w_n^{(m)}(y_m(x_n) \neq t}{\sum_{n=1}^N w_n^{(m)}} \quad (7)$$

iii. And then used evaluation

$$a_m = I_n \left\{\frac{1-\varepsilon_m}{\varepsilon_m}\right\} \quad (8)$$

c) Fixing (updating) data weights.

$$w_n^{(m+1)} = w_n^{(m)} \exp(a_m I(y_m(x_n) \neq t_n \quad (9)$$

d) Make predictions using the final model as follows:

$$Y_m(x) = sign(\textstyle\sum_{m=1}^{M} a_m y_m(x)) \quad (10)$$

The application of the adaptive boosting algorithm is applied to applications as shown in figure 3 in the form of a flowchart. The flowchart itself functions to help understand the workflow or processes that exist in the system logically using special symbols so that it is easier to identify and to analyze each system process.

Figure 5 it can be seen that the input data used in this application is the name of the tester, the name of the transformer, and the content of dissolved gas concentrations including H2, CH4, C2H2, C2H4, and C2H6. The system flow that will be applied in the transformer fault identification application is when opening the application, the main page of the system is a calculation page that functions as a transformer damage identification test. If the user is going to do a test, they can choose, if they choose to import data, the user needs to import an excel file containing the name of the tester, the name of the transformer, the method used along with the content of the dissolved gases so that the data is immediately analyzed, and if the analysis has been carried out, the message data has been successfully analyzed is displayed, for the data can be seen on the history page. Meanwhile, if the user does not import, the user needs to select the name of the tester who is responsible for the data to be tested, if the tester's name is not in the list, the user needs to add a new tester name by selecting the + Tester button, then add a new tester name. After selecting the tester name, the user selects the name of the transformer or transformer to be tested, if the transformer being tested is new, the user needs to add a new transformer name by pressing the +Trafo button and writing the new transformer name then submit. Continued by selecting the method to be used in the test, if the user chooses the DTM method, it is necessary to add data on the concentration of dissolved gases CH4, C2H2, and C2H4. Meanwhile, if you choose to use the DPM method, the data that needs to be added is H2, CH4, C2H2, C2H4, and C2H6.

After all the data has been filled in, the user presses the analysis button, so that the system will analyze the data that has been added and display the analysis results in the form of the name of the tester responsible for the test data, the name of the transformer being tested, the method used in the test, and the transformer damage point which is the name of the damage area along with a description of the cause of the damage at that point. For the DPM method, the results of the Cx and Cy calculations will be displayed in the description combined with a description of the cause of the damage. However, if the user is not going to do the test but is going to check the transformer history, then move to the history page, select the transformer name to see the list of tests that have been carried out. After that, the system will display a list of tests that have been performed on the selected transformer including the name of the selected transformer, the date of the test, the test method used (DTM or DPM), the concentration of dissolved gases tested in ppm (H2, CH4, C2H2, C2H4, and C2H6), the transformer damage point, description, and the name of the tester. The admin can export the test list according to the name of the selected transformer into an excel file.

Accuracy testing is conducted to ascertain the level of precision in the outcomes generated by the applied method in resolving a problem by assessing its error values. This testing process involves comparing the results obtained from the method with the actual values or known solutions . In accuracy testing, there are levels of diagnosis as follows (D. Nurlaela, 2020):

Table 1 Levels of Diagnosis

No	Accuracy Value	Description
1.	90-100	Excellent classification
2.	80-90	Good classification
3.	70-80	Fair classification
4.	60-70	Poor classification
5.	50-60	Failure

Table 1 delineates the Levels of Diagnosis, providing a clear correlation between accuracy values and the effectiveness of classification. A classification accuracy within this range implies a lack of effectiveness in the diagnostic process. Overall, Table 1 serves as a valuable reference tool, allowing quick and informed assessments of the diagnostic system's performance based on achieved accuracy values.

RESULT AND DISCUSSION

The result of this research is a desktop application that can identify disturbances in transformers using the DTM and DPM by applying a machine learning adaptive boosting (AdaBoost) algorithm. Accuracy testing is carried out to determine the accuracy of the results of the method applied in solving problems by finding the error value. Accuracy testing carried out in this application is divided into three types, namely accuracy testing based on the division of the number of datasets, accuracy testing based on the estimator level, and the third based on the learning rate value. The amount of data used in the test for the DTM is 1402 while for the DPM is 600 data.

Testing the comparison of training data and testing data were done to determine the effect of the ratio of the number of uses of training data and testing data on the prediction ability of Adaptive Boosting (AdaBoost) by recognizing dataset patterns. Testing was carried out 10 times to get an average accuracy value because calculations can produce different results in each execution with input data obtained randomly. In this test, there are 9 types of training data and testing data comparison scales, namely 90% - 10% with a distance range of 10% for each comparison. Testing uses the number of estimators of 100 and the learning rate value of 0.5.

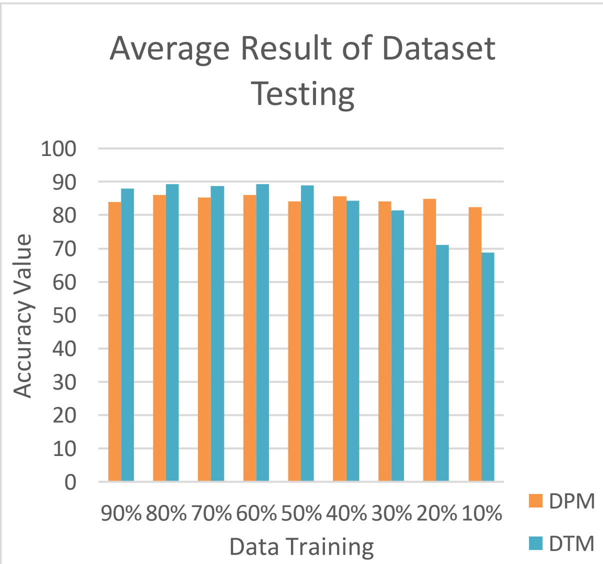

Figure 6 Graph Average Results of Dataset Testing

Figure 6 shows that the highest value of dataset usage comparison is for the DTM with 80:20 dataset comparison with an average value of 89.4, while for the DPM there are two equal average values of 86 in the 80:20 and 60:40 comparisons. After that, the second test is based on the estimator level which uses a training data and testing data comparison scale of 80:20, because from the previous test results the highest value is generated from this comparison. The learning rate value used is the default value of 1. The estimator values that will be used in this test are 100, 200, 300, 400, and 500. Testing was carried out 10 times with datasets taken randomly but the comparison of training data and testing data remained the same. The test results can be seen in Figure 7

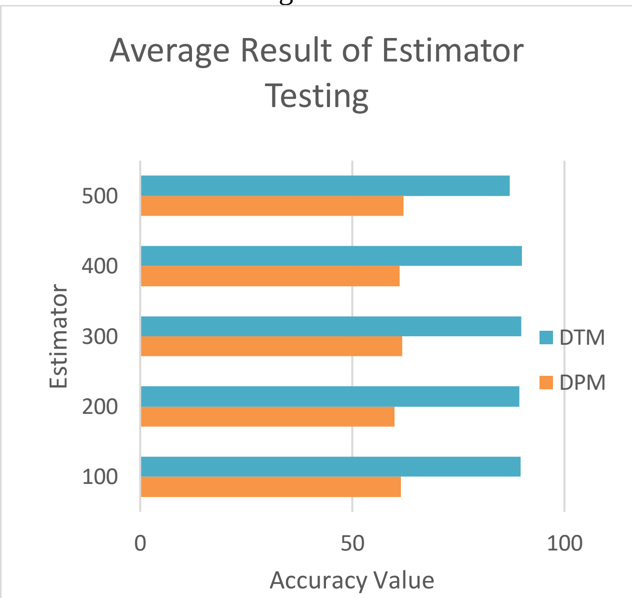

Figure 7 Graph Average Result of Estimator Testing

Figure 7 shows that the average result of accuracy testing based on the highest estimator level for the DTM is 400 with an average value of 89.9, while for the DPM is 500 with an average of 62.1. The last accuracy test is based on the level of learning rate which is a hyperparameter using a dataset ratio of 80:20 and an estimator value of 400 for the DTM and an estimator value of 500 for the DPM. The hyperparameter value or learning rate can use a value between 0.1 and 1, but the values used in this test include 0.1; 0.5; and 1, namely the lowest value of 0.1, the middle value is 0.5, and the highest value is 1 (Reichenbach et al., 2019). The test is also the same, which is carried out 10 times a trial by taking training data and testing data randomly. The results of the test based on the learning rate are in Figure 8

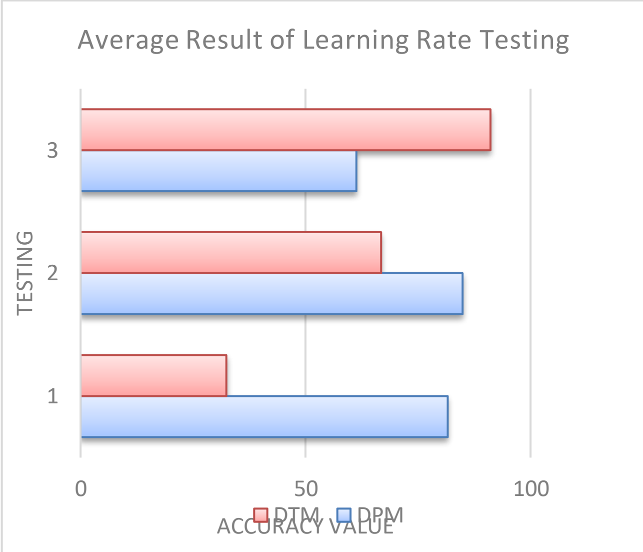

Figure 8 Graph Average Result of Learning Rate Testing

Figure 8 shows that value 1 is the learning rate of 0.1, value 2 is the learning rate of 0.5, and value 3 is the learning rate of 1. So the results of the test conducted 10 times showed the DTM the highest result at the learning rate level 1 with an average value of 91.1, while the DPM is at the learning rate level 0.5 with an average value of 84.9.

DISCUSSION

The study on enhancing transformer fault identification with the AdaBoost machine learning algorithm has yielded crucial insights directly aligned with the article's title. The results, succinctly summarized below, emphasize key aspects of accuracy testing that are imperative to advancing transformer health assessment methodologies. The first phase of accuracy testing concentrated on optimizing the dataset split, revealing that both the DPM and DTM exhibited peak performance when the dataset was divided into an 80% training and 20% testing configuration. Moving to the critical parameter of estimators, the second stage of testing demonstrated that the AdaBoost algorithm's efficacy for both DPM and DTM was maximized with 400 estimators. This finding underscores the significance of estimator selection in achieving optimal accuracy in identifying faults within transformers. The third stage, exploring the impact of the learning rate hyperparameter, provided valuable insights. For DPM, the highest average accuracy was achieved at a learning rate of 0.5, emphasizing the crucial role of this parameter in refining the AdaBoost algorithm's performance.

Conversely, the default learning rate of 1 proved to be the most effective for DTM. Combining these insights, the study determined the optimal application of the AdaBoost algorithm for transformer fault identification. For DPM, superior results were attained with an 80% training and 20% testing dataset split, 500 estimators, and a learning rate of 0.5. In parallel, DTM demonstrated optimal performance with an 80% training and 20% testing dataset split, 400 estimators, and a learning rate of 1.

These results, directly related to the article's title, underscore the significance of careful parameter selection in optimizing the AdaBoost algorithm for transformer fault identification. The findings contribute pivotal information for researchers and practitioners seeking to enhance the precision and efficiency of transformer health assessment methodologies through advanced machine learning techniques.

Future research endeavors should delve into the development of real-time monitoring systems and predictive maintenance strategies. Implementing continuous monitoring mechanisms for transformer health, coupled with predictive algorithms, could enable proactive measures to prevent failures and optimize maintenance schedules. This proactive approach has the potential to significantly reduce downtime and enhance the overall reliability of power distribution systems. In conclusion, leveraging the insights gained from this research, future endeavors should aim to push the boundaries of transformer health assessment and contribute to the ongoing evolution of power distribution systems. By addressing the outlined areas, researchers can further advance the field, ultimately leading to more reliable and resilient electrical infrastructure. The discussion section of this research is pivotal in unraveling its real-world impact, drawing comparisons with studies in different fields, and delineating potential avenues for future research.
Comparing the results of this research with studies in other fields sheds light on the broader applicability of fault diagnosis methodologies. For instance, similarities may be found in fault detection approaches used in sectors like manufacturing, aerospace, or healthcare. By examining commonalities and differences in methodologies and outcomes, valuable insights can be gleaned, leading to cross-disciplinary learning and potential adaptation of techniques for various applications.

CONCLUSION

The inference that can be made based on the research that has been done is that the design of fault identification applications in transformers using the Adaboost machine learning algorithm using the Duval Triangle Method and Duval Pentagon Method is a good solution in helping to identify damage areas in transformers. The evaluation results of testing the application of the adaboost algorithm carried out an accuracy rate of 84.9% using a dataset division of 80:20, an estimator level of 500, and a learning rate of 0.5 in the DPM method shows that it has performed classification well and 91.1% in the DTM method has shown the system has performed classification very well with a dataset division of 80:20, an estimator level of 400, and a learning rate of 1.

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