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Accuracy Improvement of Data-Driven Algorithms in Power Transformer Assessment Using Hyperparameter Optimization on DGA Data

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Abstract

Transformers are critical components in power systems. Faults within these devices can lead to substantial repair costs and prolonged service interruptions. Dissolved Gas Analysis (DGA) of transformer oil is widely used for monitoring transformer health. This research leverages data-driven algorithms, employing the Duval-Pentagon (DP) method and hyperparameter optimization, to enhance fault diagnosis accuracy in power transformers. After preprocessing the DGA dataset, it was split into training and testing sets in an 80:20 ratio. Subsequently, several data-driven algorithms, including Support Vector Machines Algorithm (SVMA), Decision Tree Algorithm (DTA), Logistic Regression Algorithm (LRA), and Naive Bayes Algorithm (NBA), were employed on the dataset. A significant challenge was the inherent limitations of DGA accuracy under varying operational conditions and the presence of outliers in the dataset. A robust technique was implemented alongside a random search for hyperparameter optimization to address this challenge to improve model resilience and diagnostic accuracy. Evaluation metrics such as accuracy, F1-measure, recall, precision, and Matthews Correlation Coefficient (MCC) were used to assess impact of hyperparameter optimization. The findings demonstrate that hyperparameter optimization consistently enhances the performance of data-driven algorithms. Among the algorithms proposed in this research, DTA with hyperparameter optimization achieved the highest accuracy with an accuracy rate of 93.37% in transformer fault diagnosis. The algorithms were implemented based on Python.

Keywords: Optimization, Power Transformer, Decision Tree, Machine Learning, Fault Diagnosis.
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1. Introduction

Power transformers are critical assets in the energy distribution and transmission infrastructure due to their high cost and indispensable role in the production-to-consumption chain. Given their importance, meticulous and ongoing monitoring is essential. It has long been established that abnormal conditions, such as short circuits, can lead to gas generation within oil-filled electrical equipment, especially transformers. When short circuits occur, the combination of oil and cellulosic insulation experiences thermal and electrical stress, resulting in the sublimation and decomposition of gases. Dissolved Gas Analysis (DGA) remains the most prevalent technique for assessing the health of power transformer [1, 2].

Dissolved Gas Analysis provides the analytical basis for a diverse range of interpretation approaches, including Roger’s ratio methods, the IEC 60599 standard, and Dorneneburg’s method [3-6]. Among these methods, graphical techniques such as the Duval-Triangle (DT) and Duval-Pentagon (DP) serve as complementary tools in this analytical process. The DT technique is widely used; nevertheless, studies have shown that the DP technique is more effective for resolving specific types of issues and exhibits superior accuracy in fault detection within power transformers [7, 8].

In recent years, artificial intelligence (AI) techniques have gained prominence for diagnosing and detecting faults in transformers. Machine learning (ML) and deep learning (DL) approaches have been explored extensively. In [9], the authors introduced a transformer fault diagnosis approach that combines backpropagation neural networks and SVM, achieving a diagnosis accuracy of 92% based on DGA data. This enhanced accuracy contributes to the reliable, safe, and sustainable operation of power grids. A wide-ranging works review exploring the application of AI techniques for dissolved gas analysis -based fault detection and the resolution of complex challenges in early transformer fault detection is investigated in [10]. This assessment encompasses neural networks, clustering, and support vector machines.

In [11], an advancement involves an advanced diagnostic prediction technique that combines deep neural networks with synthetic minority oversampling methods. This approach demonstrates significant advantages over traditional classification methods when dealing with imbalanced datasets. [12] has explored ML algorithms such as decision trees (DT), SVMs, and k-nearest neighbors to leverage AI-driven data augmentation strategies for enhancing fault diagnosis performance in power transformers. This approach has shown promise in enhancing fault diagnosis performance, especially for minority class faults within power transformers.

In [13], the common vector approach is described as an effective classifier for scenarios with limited data. The feature vector needed for CVA training and testing phases is constructed with both raw DGA data and derived characteristics. The proposed method's performance is evaluated on DGA datasets provided by the Turkish Electricity Transmission Company and comparation with conventional approaches in terms of organization accuracy and training/testing duration. In [14], a deep belief network using DGA method is studied for diagnosing faults and states in power transformers using customized input features. This research focuses on six fault classifications based on nine characteristics extracted from the gases dissolved in the insulating oil of power transformers. The deep belief network was assessed by samples collected from power transformers. In [15], a fuzzy logic approach is developed to evaluate the condition of power transformers using three DGA methods: the key gas method, IEC three-gas ratio method, and Duval triangle method. The fuzzy logic approach assesses the percentage of the failure index and determines internal faults. The performance of the fuzzy logic approach was evaluated on DGA results from two transformers and was practically confirmed by an un-tanked power transformer exhibiting arcing at the core in both cases. In [16], a convolutional neural network model is provided that is capable of identifying various transformer fault types even in the presence of varying levels of noise in measurement data. To simulate real-world conditions, noise was artificially introduced into all dissolved gas analysis samples at levels ranging up to 20%.

Despite numerous applications of AI algorithms for fault detection in power transformers, hyperparameter tuning has predominantly relied on traditional trial-and-error methods. Moreover, the previous research often utilized feature scaling techniques like min-max scaling or z-score normalization, which exhibit limited resilience to outliers within DGA datasets. To overcome these limitations, this study introduces a data-driven algorithm where hyperparameters are optimized using random search technique, with the goal of improving the accuracy of transformer fault prediction under DGA data. Furthermore, robust scaling is implemented to enhance the algorithm's robustness to the presence of outliers in the DGA dataset. The remainder of this paper is structured as follows. Section 2 discusses Dissolved Gas Analysis (DGA) in transformer oil, and Duval Pentagon technique. In Section 3, the DGA dataset and the proposed algorithms are introduced. Section 4 presents the experimental results and provides a detailed analysis. Finally, Section 5 concludes the research.

2. Dissolved gas analysis in power transformer oil

Dissolved Gas Analysis is a robust and widely utilized diagnostic technique for detecting faults in oil-filled transformers. Due to thermal and electrical stresses, the oil in power transformers may degrade, resulting in the release of the gases, involving hydrogen, carbon dioxide, ethane, carbon monoxide, ethylene, methane, and acetylene [17]. Numerous approaches are employed to analyze dissolved gases and interpret faults in power transformers, such as the Rogers Ratio, Doernenburg Ratio, Duval Triangle (DT), IEC Standard Code, and Duval Pentagon (DP) [4-6]. In this paper, the DP technique is applied, which identifies seven fault types: D1, D2, PD, S, T1, T2, and T3, as depicted in Table 1. Furthermore, the number of instants associated by the fault is presented in this table.

The calculations for the DP technique involve determining the percentage of each gas concentration (in ppm) relative to the total gas concentration. The percentage concentration of the total sum was also utilized, where each sample $X = [x_1, x_2, x_3, x_4, x_5]$ is scaled as follows:

$$X = \frac{X}{\sum_{i=1}^{5} x_i} \times 100\% \tag{1}$$

where x_1, x_2, x_3, x_4, and x_5 represent the gases such as hydrogen, methane, ethane, ethylene, and acetylene, respectively.

Table.1.
Transformer Fault Detection Using the Duval Pentagon Technique

No.	***Type of Fault***	***Short Name***	***Sample***
1	Low-energy electrical discharges	D1	233
2	High-energy electrical discharges	D2	237
3	Corona-type partial discharge	PD	241
4	Stray gassing of mineral oil	S	227
5	Thermal faults at temperature range < 300°C	T1	239
6	Thermal faults at temperature range between 300 °C and 700 °C	T2	241
7	Thermal faults at temperature range > 700 °C	T3	240

3. Materials and Methodologies

The following subsections comprehensively delve into the relevant background DGA data and the research methodology employed in this study.

A) Dissolved Gas Analysis Dataset

In this study, a dissolved gas analysis dataset comprising 1658 samples is employed to identify and diagnose several faults in oil-immersed transformers. The dataset includes five input features representing gases: ethane, methane, hydrogen, ethylene, and acetylene, as well as seven target fault classes: PD, S, D1, T1, D2, T2, and T3 [2]. The distribution of instants for each transformer fault is detailed in Table 1, with its pie chart and bar plot representations visualized in Figure 1.

In the following sections survey the preprocessing steps of the DGA dataset, feature scaling, and the division of the dataset into training and testing sets in this study.

Following the initial assessment of the DGA dataset, procedures for handling missing values and outliers are addressed. Subsequently, normalization is applied to the dataset. To accelerate the convergence of the training model and reduce the impact of varying feature scales, it is essential to apply data scaling to the extracted features, leading to minimized dimensional disparities among them. Although the most previous studies have utilized conventional normalization techniques such as standard scaling or min-max scaling, this research adopts the robust scaling technique due to the presence of outliers. This approach is intended to improve the performance of the proposed algorithms. The formula for robust scaling is presented in Equation 2.

$$x_{scaled} = \frac{x - median(x)}{IQR} \times 100\% \quad (2)$$

here, x , and x_{scaled} denote the original data and the scaled data, respectively. Moreover, IQR refers the Interquartile Range, which is the difference between the first quartile and the third quartile [18].

The DGA dataset is then divided into training and testing sets in an 80:20 split, assigning 1326 samples to the training set and using the remaining samples for testing. This setup is applied to assess the performance of the data-driven algorithms outlined in paper. The DGA dataset was split by leveraging the Scikit-learn framework in Python. The sample distribution for each fault category in the training and testing sets is as follows: In the training set, the counts are 193 for T3, 192 for S, 182 for PD, 193 for D1, 186 for T1, 191 for D2, and 189 for T2. For the testing set, there are 45 samples for S, 48 for PD, 47 for D1, 48 for T1, 48 for D2, 48 for T2, and 48 for T3.

The flowchart outlining data-driven algorithms for fault prediction of power transformers is depicted in Figure 2.

B) Data-Driven Algorithms

Following data preprocessing, normalization using robust scaling and random splitting into training and test sets, various ML methods are applied to the DGA data. This study compares and assesses data-driven algorithms, including the

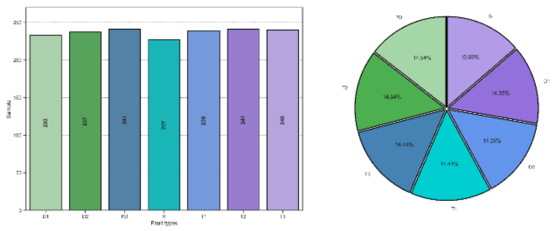

Fig. 1. Distribution of Faults in Transformer Oil

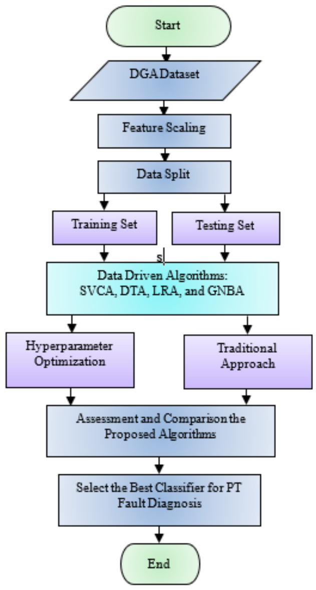

Fig. 2. Flowchart of the Data-Driven Algorithms Process

Decision Tree Algorithm (DTA), Support Vector Machine Algorithm (SVMA), Logistic Regression Algorithm (LRA), and Naïve Bayes Algorithm (NBA), for detecting faults in oil transformers. The five data-driven algorithms employed in this study are listed below:

SVMA:Support Vector Machine Algorithm (SVMA) is one of the well-known ML methods in the supervised learning domain, is applicable to both classification and regression tasks. SVMA is particularly effective in scenarios involving small sample sizes, nonlinearity, and high-dimensional data. In [19], SVMA was applied to classify power transformer faults and to choose the most appropriate gas from traditional DGA methods. SVMA has been successfully in solving fault classification problems by identifying an optimum separating hyperplane that maximizes the margin between distinct data classes. The performance of SVMA is contingent upon the training dataset and the selection of Kernel functions. The hyperparameters optimized for the SVMA included regularization parameter, class weight, kernel coefficient, and kernel type.

DTA:Decision tree algorithms (DTA) is a widely employed data mining method utilized for constructing classification systems for developing predictive methods targeting specific variables. This method segments a population into tree-like branches, forming an inverted tree structure consisting of a root node, internal nodes, and leaf nodes. As a non-parametric technique, it can proficiently handle large and complex datasets without the need for imposing a rigid parametric framework. When sample sizes are sufficiently large, the data can be partitioned into training and validation sets. The training set is utilized to build the DT model, while the validation set is applied to determine the optimal tree size, ensuring the final method's optimality [20]. The optimized hyperparameters for the DTA included criterion (Gini or Entropy), minimum number of samples per leaf, maximum features, and splitter type.

LRA:The logistic regression algorithm (LRA) is extensively utilized in many applications to enhance ML techniques, particularly in situations involving discrete and historical data, such as DGA. Given that LRA is designed for classifying data into distinct categories, it proves to be an optimum technique for DGA applications. Overfitting can become a challenge in supervised learning models, specifically when there are many input features. To address this, regularized logistic regression methods are generally used, as they mitigate the overfitting problem by employing a cost function optimized through logistic regression. Regularization not only prevents overfitting produced by either a limited training dataset or a high number of features, but it also supports in proper attribute choice by filtering out irrelevant attributes [21]. The optimized hyperparameters for the LRA comprised the regularization strength, the class weight, solver method, regularization type, and maximum iterations.

NBA:Naïve Bayes Algorithm (NBA) is a statistical ML technique based on Bayes' Theorem, which assumes that features are mutually independent in the classification process.

$$P(A|B) = \frac{P(B|A).P(A)}{P(B)} \qquad (3)$$

In Equation (3), $P(A|B)$ indicates the conditional probability of A given B, while $P(B|A)$ signifies the conditional probability of B given A. $P(A)$ and $P(B)$ are the prior probabilities of A and B, respectively [22]. The optimized hyperparameters for the NBA contained smoothing parameter, the class priors, and the distribution type.

C) Hyperparameter Optimization

Hyperparameter tuning is a crucial step in enhancing and optimizing the performance of data-driven algorithms. In this subsection, two stages are considered:

- In the first stage, the traditional fault prediction for power transformers oil is presented without employing a hyperparameter tuning strategy. Therefore, the default parameters of each data-driven algorithms are applied to assess their performance.
- In the second stage, the proposed algorithms utilize random search and cross-validation techniques to optimize and fine-tune the hyperparameters. Hyperparameter tuning is a significant research challenge in ML algorithms, as it straight effects the performance of algorithms. Appropriate tuning or optimization of hyperparameters is expected to lead to enhanced the algorithms performance. Random search is predominantly efficient when the hyperparameter space is large and computationally expensive to explore comprehensively.

D) Evaluation Criteria

Implementation of the proposed data-driven algorithms was performed by leveraging Python code to assess their performance across several criteria, including precision, recall, accuracy, F1-measure, and Matthews Correlation Coefficient (MCC), as formally defined in Equations (4) through (8):

$$Precision\ (\%) = \frac{TP}{TP + FP} \times 100 \qquad (4)$$

$$Recall\ (\%) = \frac{TP}{TP + FN} \times 100$$
$$Accuracy\ (\%) = \frac{TP + TN}{TP + FP + TN + FN} \times 100$$
$$F1 - measure\ (\%) = 2 \times 1/((1\ /\ Precision) + (1\ /\ Recall)\ ) \times 100$$
$$MCC\ (\%) = (TP \times TN - FP \times FN)/\sqrt{}((TP + FP)(TP + FN)(TN + FP)(TN + FN)) \times 100$$

where, TP, TN, FP, and FN signify true positive, true negative, false positive, and false negative, respectively. Furthermore, an in-depth assessment of the data-driven algorithms was performed through the utilization of Area Under Curve (AUC), Receiver Operating Characteristic (ROC) curve, and confusion matrix to provide a comprehensive analysis of their efficiency [2, 11, 23].

4. Results and discussion

Following the preprocessing steps of the DGA dataset, including feature scaling and the splitting of the dataset into training and testing sets, the proposed algorithms were applied in two phases. In this section, the performance of the four proposed algorithms is assessed by hyperparameter optimization techniques, based on the criteria introduced in the previous subsection.

Firstly, the four proposed algorithms including Decision Tree Algorithm (DTA), Support Vector Classification Algorithm (SVCA), Logistic Regression Algorithm (LRA), and Naive Bayes Algorithm (NBA), were compared using traditional technique. Metrics such as accuracy, F1-measure, precision, Matthews Correlation Coefficient (MCC), and recall were employed. The results are presented in Table 2 and compared in Figure 3. As observed, the DT algorithm performs the best among the proposed algorithms, achieving an accuracy of 92.77%, an F1-measure of 92.79%, precision of 92.91%, recall of 92.77%, and MCC of 91.54%.

In the subsequent phase, the hyperparameter optimization technique was applied using Random Search for the proposed algorithms to enhance fault detection in power transformers. The performance of the four proposed algorithms was assessed with the same criteria, as shown in Table 3, and compared in Figure 4. The results indicate that all proposed algorithms with Random Search outperformed those using traditional methods. Among them, the DTA algorithm showed the best performance, with an accuracy of 93.37%, an F1-measure of 93.41%, precision of 93.77%, recall of 93.37%, and MCC of 92.28%.

The hyperparameters optimized during this process included specific parameters for each algorithm. For the DTA, parameters such as criterion (Gini or Entropy), splitter type (best or random), minimum samples per leaf (1, 2, 5, 10, or 20), and maximum features (auto, sqrt, or log2) were adjusted. In the case of the SVMA, key parameters optimized included the regularization parameter (C), kernel coefficient (gamma), and kernel type (linear, rbf, or poly). For the LRA, the optimized parameters encompassed regularization strength (C), solver method (newton-cg, lbfgs, or liblinear), and maximum iterations (100, 200, or 300). Lastly, for the NBA, variance smoothing was optimized using a logspace approach. This systematic optimization process allowed for a comprehensive exploration of parameter combinations through cross-validation, significantly contributing to improved diagnostic

Table.2.
Evaluation of Data-Driven Algorithms' Performance

Algorithms	***Criteria***				
	Accuracy (%)	***Precision (%)***	***Recall (%)***	***F1-measure (%)***	***MCC (%)***
NBA	57.23	58.84	57.23	54.97	50.65
LRA	77.71	82.49	77.71	79.09	74.46
SVCA	90.36	91.89	90.36	90.68	88.87
DTA	92.77	92.91	92.77	92.79	91.54

Table.3.
Evaluation of Data-Driven Algorithms' Performance using hyperparameter optimization approach

Algorithms	***Criteria***				
	Accuracy (%)	***Precision (%)***	***Recall (%)***	***F1-measure (%)***	***MCC (%)***
NBA	57.83	59.04	57.83	55.22	51.41
LRA	80.42	83.35	80.42	81.07	77.42
SVCA	91.87	93.49	91.87	92.20	90.67
DTA	93.37	93.77	93.37	93.41	92.28

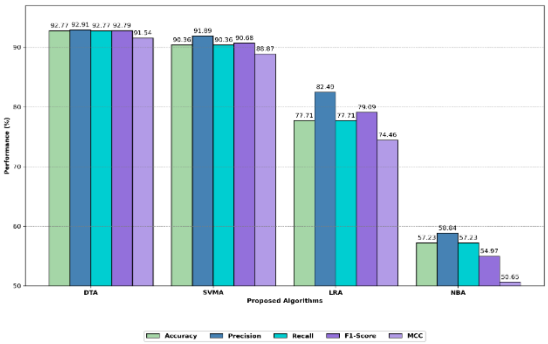

Fig. 3. Performance Comparison of Data-Driven Algorithms Applied to Dissolved Gas Analysis Data

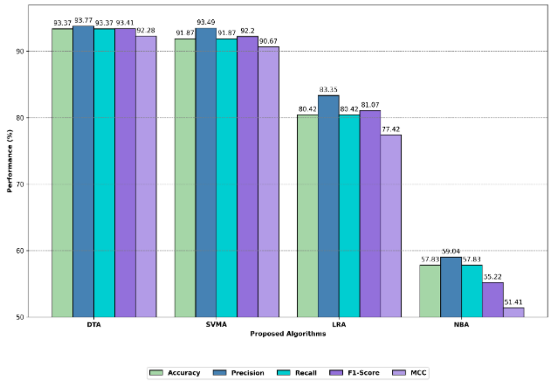

Fig. 4. Performance Comparison of Data-Driven Algorithms on Dissolved Gas Analysis Data Using a Hyperparameter Optimization Approach

accuracy across all algorithms. The findings underscore the importance of hyperparameter tuning in enhancing model performance and ensuring reliable fault diagnosis in power transformers. For a more detailed evaluation of the proposed algorithms in classifying faults in oil-immersed power transformers, both with and without hyperparameter optimization techniques, ROC curves were utilized. Figures 5 and 6 present the ROC curves for the data-driven methods using traditional, and hyperparameter optimization techniques, respectively. It is evident that the DT algorithm consistently performs the best among the proposed algorithms in both techniques.

Additionally, for a more comprehensive comparison, the line plots of MCC and AUC are shown in Figures 7 and 8, respectively, highlighting the superiority of the DTA algorithm over other data-driven algorithms in this study.

To further examine the performance of the DTA algorithm, confusion matrices with traditional and hyperparameter optimization techniques are depicted in Figures 9 and 10, respectively, confirming the DT algorithm's effectiveness.

5. Conclusion

In this paper, several data-driven algorithms for fault diagnosis in transformers are examined employing Dissolved Gas Analysis (DGA) technique. To evaluate the results using classifier metrics, both traditional and hyperparameter optimization techniques were applied to all proposed algorithms, including Decision Tree Algorithm (DTA), Support Vector Machine Algorithm (SVMA), Logistic Regression Algorithm (LRA), and Naive Bayes Algorithm (NBA). The first stage, employing traditional technique on the proposed algorithms, demonstrated that the DTA achieved the highest performance. In the second stage, the application of hyperparameter optimization through random search further improved the performance of the algorithms, with notable enhancements in metrics such as F1-measure, precision, recall, Matthews Correlation Coefficient (MCC), Area Under Curve (AUC), and Receiver Operating Characteristic (ROC) curve. By leveraging hyperparameter optimization technique, the DT algorithm achieved the best performance among the proposed algorithms, with an accuracy of 93.37% for fault detection in power transformers. Future research could explore the use of deep learning algorithms combined with alternative hyperparameter optimization techniques to further enhance fault diagnosis in oil-immersed transformers.

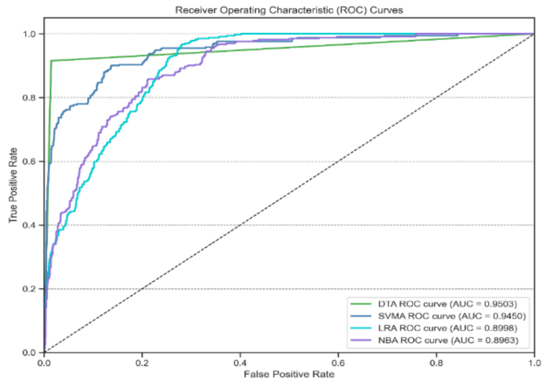

Fig. 5. Receiver Operating Characteristic Comparison of Data-Driven Algorithms

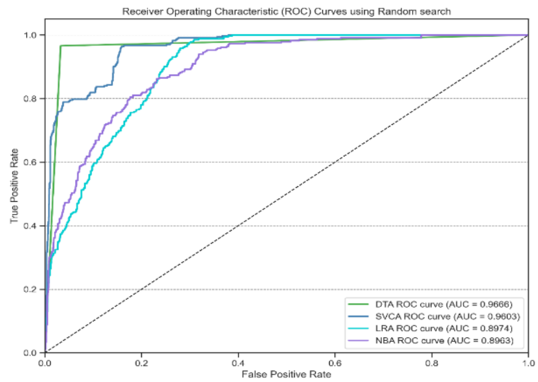

Fig. 6. Receiver Operating Characteristic Comparison of Data-Driven Algorithms with Hyperparameter Optimization

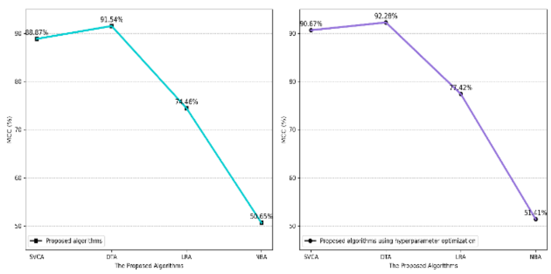

Fig. 7. Comparison of Matthews Correlation Coefficient for Data-Driven Algorithms

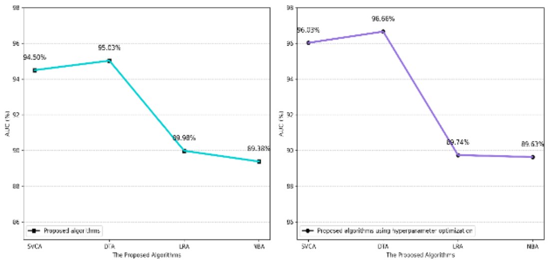

Fig. 8. Comparison of Area Under Curve for Data-Driven Algorithms

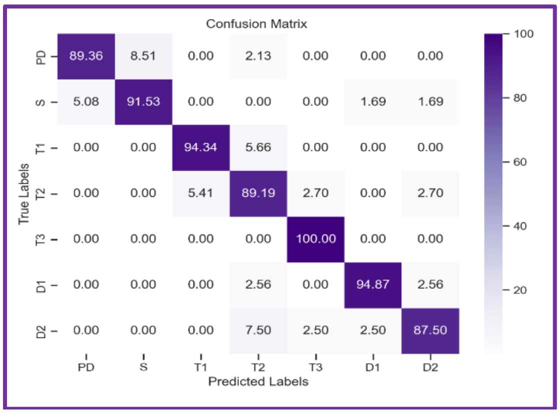

Fig. 9. Confusion Matrix for Decision Tree Algorithm

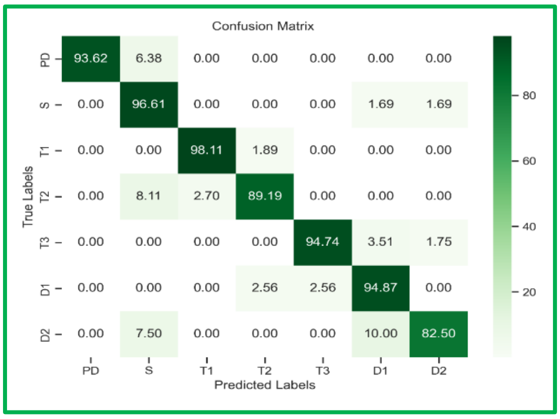

Fig. 10. Confusion Matrix for Decision Tree Algorithm with Hyperparameter Optimization

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