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Comparative analysis of machine learning algorithms for schizophrenia detection

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ABSTRACT

As mental and neurological disorders continue to rise globally, research utilizing artificial intelligence to analyse and classify differences in EEG signals is growing rapidly. This study utilises six machine learning algorithms for detecting schizophrenia (SZ) using multichannel EEG signals. In the initial phase of this study, pre-processing is carried out, followed by the application of 13 distinct feature extraction techniques. The extracted features are subsequently classified using various machine learning algorithms, leading to classification accuracies up to 1.00 in four algorithms including Decision Tree, Random Forest, Support Vector Machines (SVM) and Gradient Boosting. In addition, 5-fold cross-validation is applied to increase the reliability of the study. The findings indicate that the study achieved remarkable success and demonstrates the potential for effectively detecting schizophrenia using EEG signals.

Şizofreni tespiti için makine öğrenmesi algoritmalarının karşılaştırmalı analizi

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ÖZET

Zihinsel ve nörolojik bozukluklar küresel olarak artmaya devam ederken, EEG sinyallerindeki farklılıkları analiz etmek ve sınıflandırmak için yapay zekadan yararlanan araştırmalar hızla artmaktadır. Bu çalışmada, çok kanallı EEG sinyallerini kullanarak şizofreniyi (SZ) tespit etmek için altı farklı makine öğrenimi algoritması kullanılmaktadır. Bu çalışmanın ilk aşamasında, ön işleme gerçekleştirilmekte ve ardından 13 farklı özellik çıkarma tekniği uygulanmaktadır. Çıkarılan özellikler daha sonra çeşitli makine öğrenimi algoritmaları kullanılarak sınıflandırılmış ve Karar Ağacı, Rastgele Orman, Destek Vektör Makineleri (DVM) ve Gradyan Güçlendirme olmak üzere dört algoritmada 1.00'e varan sınıflandırma doğrulukları elde edilmiştir. Ayrıca, çalışmanın güvenilirliğini artırmak için 5 kat çapraz doğrulama uygulanmıştır. Bulgular, çalışmanın kayda değer bir başarı elde ettiğini ve EEG sinyallerini kullanarak şizofreniyi etkili bir şekilde tespit etme potansiyelini ortaya koyduğunu göstermektedir.

1. INTRODUCTION

Schizophrenia (SZ) is a chronic and severe mental disorder that affects how a person thinks, feels, and behaves. Characterized by symptoms such as hallucinations, delusions, and cognitive impairments, it poses significant challenges for diagnosis and treatment[1]. According to the World Health Organization (WHO), schizophrenia is a serious condition that affects over 21 million people globally[2]. However, the WHO has also indicated that schizophrenia is treatable, and early or post-diagnosis interventions can help determine its severity and stage. Identifying and treating schizophrenia is crucial, as it significantly disrupts thinking,

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memory, perception, and various daily activities. Traditional diagnostic methods rely heavily on clinical interviews and symptom assessments, which can be subjective and time-consuming. In recent years, there has been a growing interest in leveraging technological advancements to improve the accuracy and efficiency of schizophrenia diagnosis.

One promising approach involves the use of electroencephalography (EEG) signals. EEG is a non-invasive method that records electrical activity of the brain, providing real-time insights into neural function. It has been widely used in the study of various neurological and psychiatric disorders. The complexity and high-dimensional nature of EEG data, however, present substantial challenges for traditional analytical techniques[3].

This is where deep learning comes into play. Deep learning, a subset of machine learning, employs neural networks with multiple layers to automatically learn and extract features from complex datasets. It has demonstrated remarkable success in fields such as image and speech recognition, natural language processing, and biomedical signal analysis. Applying deep learning to EEG data for the detection of schizophrenia holds great promise, potentially leading to more accurate, objective, and rapid diagnostic tools[4].

1.1. Related Work

One of the studies which focuses on detection of SZ employed a hybrid framework that integrated brain effective connectivity images derived from EEG signals with pre-trained CNN-LSTM models to differentiate schizophrenia (SZ) patients from healthy controls. Utilizing Transfer Entropy (TE) to estimate directed causalities in brain information flow from EEG signals, the study achieved an accuracy of 99.90% with the EfficientNetB0-LSTM model, outperforming previous SZ detection studies. TE effective connectivity images revealed differences in information flow between SZ patients and healthy individuals, with SZ patients showing lower information flow values across most brain channels compared to healthy subjects. These findings suggest that SZ patients have reduced TE (information flow) in various brain channels, indicating potential differences in brain functionality between SZ patients and normal individuals. Overall, the hybrid model excelled in analyzing brain function and detecting SZ patients, demonstrating its effectiveness in distinguishing SZ patients from healthy controls based on EEG signals[5].

A research study introduces the use of Multivariate Empirical Mode Decomposition (MEMD) for detecting Schizophrenia (SZ) from multichannel EEG signals, coupled with entropy measures computed from the Intrinsic Mode Function (IMF) domain. Five entropy measures—Approximate entropy, Sample entropy, Permutation entropy, Spectral entropy, and SVD spectral bands of EEG—were derived from the IMF signal, revealing significant differences between SZ and normal subjects ($p < 0.01$). Advanced machine learning classifiers, including Naive Bayes, Linear Discriminant Analysis, Support Vector Machine (SVM), K-Nearest Neighbour, Random Forest, and Gradient Boosting Machine, were trained on the feature matrix obtained from these entropy measures. Among these, the SVM with a Radial Basis Function (SVM-RBF) kernel showed robust classification performance, achieving an overall accuracy of 93% and an F1-score of 93.04% using 95 features. Furthermore, the study reported a detection accuracy of 90.66% for SVM when utilizing a reduced feature set of 20 features, demonstrating the method's effectiveness even with a minimal number of features for SZ detection. This research outperformed some related studies in SZ detection accuracy and underscored the potential of calculating entropy measures from the IMF domain, highlighting the capability of MEMD in managing multichannel EEG for SZ detection[6].

The study developed an Automated Diagnostic Tool (ADT) that utilizes nonlinear feature extraction from EEG signals, t-test based feature selection, and validation across various classifiers. The SVM with Radial-Basis-Function (SVM-RBF) classifier achieved the highest accuracy of 92.91%, outperforming other classifiers used in the research. The SVM-RBF classifier exhibited superior performance with an average accuracy of 92.91% in distinguishing normal EEG patterns from those of individuals with schizophrenia, highlighting its effectiveness in classifying the two groups. The findings suggest that the proposed technique efficiently differentiates between normal EEG patterns and those associated with schizophrenia, demonstrating the potential for automated schizophrenia detection using nonlinear signal processing methods. Future research directions include exploring the use of CNN deep learning models in combination with cloud computing for more effective schizophrenia diagnosis, aiming to streamline the feature extraction and selection process to enhance diagnostic accuracy[7].

The paper reported experimental results evaluating a local descriptors-based approach for detecting schizophrenia (SZ) using EEG signals, achieving high classification accuracy on two datasets: 92.85% on Dataset-1 and 99.36% on Dataset-2. The methodology involved representing EEG signals using the histogram of local variance (HLV) and symmetrically weighted-local binary patterns (SLBP) for feature extraction. A correlation-based feature selection algorithm was then applied, followed by classification using an

AdaBoost classifier. The results demonstrated that features extracted from EEG channels in the temporal lobe were particularly effective in capturing regional variations in EEG signals for SZ detection[8].

In other paper a method is proposed for detecting schizophrenia (Sz) by analysing multi-channel electroencephalogram (EEG) signals. The proposed approach uses multivariate iterative filtering (MIF) to decompose multi-channel EEG data into multivariate intrinsic mode functions (MIMFs). These IMFs are grouped based on their mean frequency to separate EEG rhythms (delta, theta, alpha, beta, gamma) from the signals. Features, such as Hjorth parameters, are then extracted from these EEG rhythms. The extracted features are ranked using a student t-test, and the 30 most discriminative features are selected for classification. Different classifiers, including K-nearest neighbours (K-NN), linear discriminant analysis (LDA), and support vector machine (SVM) with various kernels, are used to classify Sz and healthy EEG patterns. The method is applied to 19-channel EEG signals recorded from 14 paranoid Sz patients and 14 healthy subjects. The highest accuracy achieved is 98.9% using the SVM (Cubic) classifier, with sensitivity, specificity, positive predictive value (PPV), and area under the ROC curve (AUC) of 99.0%, 98.8%, 98.4%, and 0.999, respectively. The proposed MIF approach is computationally more efficient than other multivariate signal decomposition algorithms. This paper presents an efficient framework for decomposing multivariate signals and accurately detecting Sz[9].

Study of Sahu et al. the proposed network utilizes depth-wise separable convolution and attention networks at both high and low levels to combine features from 2-D scalogram images obtained through continuous wavelet transform. Depth-wise separable convolutions contribute to creating a lightweight framework, while attention techniques focus on significant features and eliminate unnecessary computations by filtering out irrelevant features. The proposed method achieves an average classification accuracy of 99% on the IBIB-PAN dataset and 95% on the EEG data from the basic sensory task in the SZ dataset. Additionally, statistical hypothesis testing using Wilcoxon’s Rank-Sum test confirms the model's performance, demonstrating that SCZ-SCAN is statistically more efficient than nine state-of-the-art methods. Experimental results indicate that PSFAN outperforms 11 contemporary methods, highlighting its effectiveness for medical industrial applications[4].

Another paper introduced a novel framework for automatic schizophrenia detection by extracting graphical features from EEG signals. This approach achieved high classification accuracy using both KNN and GRNN classifiers. Noise cancellation of EEG channels was performed using the MSPCA method, followed by the application of the PSD technique to plot EEG signals in Cartesian space. Fifteen graphical features were extracted to quantify the chaotic behavior of PSD. Among these features, the SDHC feature exhibited the highest AUC value for detecting schizophrenia using a KNN classifier. The Cz channel showed the highest classification accuracy, suggesting its potential as a biomarker for diagnosing the disorder. The study achieved an average classification accuracy of 94.80%, a sensitivity of 94.30%, and a specificity of 95.20% using the KNN classifier with City-block distance, demonstrating the effectiveness of the proposed framework for automatic schizophrenia diagnosis [10].

In the study of Prabhakar It is aimed to classify schizophrenia EEG signals using optimization algorithms and feature extraction techniques such as PLS Nonlinear Regression, EM-PCA, and Isomap. Four optimization algorithms were utilized: Flower Pollination, Eagle Strategy, Backtracking Search, and Group Search Optimization. The findings showed high classification accuracy for both normal and schizophrenia cases, with up to 98.77% accuracy achieved through specific combinations of features and classifiers. Additionally, the Naive Bayesian Classifier was optimized using the bag-of-token model, enhancing the classification process for schizophrenia cases. Overall, the research highlighted the effectiveness of nature-inspired optimization algorithms in accurately classifying schizophrenia EEG signals, presenting a promising approach for future studies in this field [11].

Shoeibi et al. introduced intelligent deep learning methods for the automatic diagnosis of schizophrenia using EEG signals, achieving a high accuracy of 99.25% with the CNN-LSTM model. Various conventional machine learning methods were compared with deep learning models, including LSTMs, 1D-CNNs, and 1D-CNN-LSTMs, for schizophrenia diagnosis. The CNN-LSTM architecture, utilizing a ReLU activation function and z-score combined normalization, outperformed other models, demonstrating superior performance. A k-fold cross-validation method with k = 5 was used for all simulations, ensuring the robustness and reliability of the results[12].

2. MATERIALS AND METHODS

2.1. Dataset

For this study, a publicly available dataset is utilized from the Institute of Psychiatry and Neurology in Warsaw Poland [13]. The dataset includes EEG recordings from 14 patients (seven males with a mean age of 27.9 ± 3.3 years, and seven females with a mean age of 28.3 ± 4.1 years) diagnosed with paranoid schizophrenia according to the ICD-10 criteria. The control group comprises EEG recordings from 14 healthy individuals (seven males with a mean age of 26.8 ± 2.9 years, and seven females with a mean age of 28.7 ± 3.4 years). EEG data were collected for 15 minutes using 19 channels, with electrode placement following the 10-20 international system. The specific positions recorded were Fp1, Fp2, F7, F3, F4, F8, T3, C3, C2, C4, T5, P3, Pz, P4, T6, O1, O2, and FCz (reference electrode), with a sampling rate of 250 Hz [14].

2.2. Pre-processing

Preprocessing transforms raw data into a suitable format to improve analysis and usability. The first step involves applying a filter to eliminate electrical noise from the raw EEG signals[4]. In this study, the datasets used have already undergone filtering to eliminate electrical noise. Therefore, the filtering step is omitted in this analysis. Normalization was performed using the StandardScaler method, which adjusts the data to have a mean of 0 and a standard deviation of 1. This process is crucial for machine learning models, as features with varying scales can otherwise negatively impact model performance. Principal Component Analysis (PCA) then applied to the data in order to reduce the size. This step helps to process the data and achieve faster results as well as eliminating meaningless and unnecessary data.

2.3. Feature Extraction

EEG signals are unstable and fluctuate unpredictably depending on brain activity. It is well known that pathological brain conditions result in a different level of randomness in EEG signals compared to those of healthy individuals[6]. In the literature different feature extraction methods are used for EEG signal classification. In this study, different feature extraction techniques were tested and the methods that gave promising results are listed as follows: Percentile, mean absolute, singular value decomposition, mean, standard deviation, variance, median, minimum, maximum, sum, kurtosis, skewness and slope sign change. Violin plots giving the intensity distribution of the features used in this study for each class are given in Figure 1.

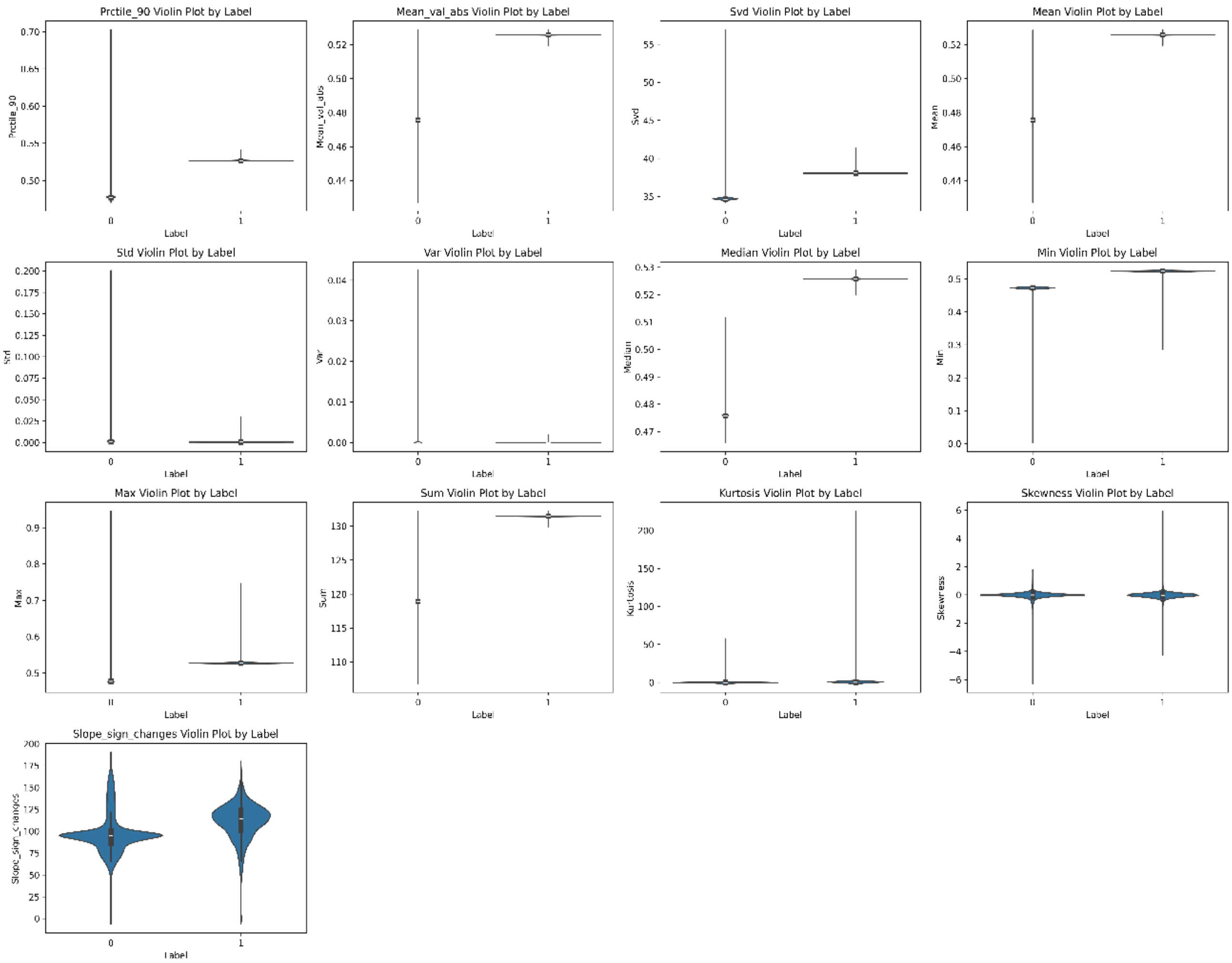

Figure 1. Violin plots of used features.

2.4. Classification

In the classification process, six distinct classification algorithms were employed to ensure a comprehensive evaluation of model performance. These methods include logistic regression, decision tree, random forest, k-nearest neighbors (kNN), support vector machine (SVM), and gradient boosting. Each algorithm offers unique advantages: logistic regression provides interpretability, decision trees offer simplicity, random forests enhance robustness through ensemble learning, kNN is effective in instance-based learning, SVM excels in handling high-dimensional spaces, and gradient boosting combines multiple weak learners for high predictive accuracy. This diversity of models allows for a thorough comparison and optimization of classification performance.

3. RESULTS AND DISCUSSION

In this study, SZ and healthy subject EEG signal classification is performed using machine learning algorithms, following the preprocessing and feature extraction steps described earlier. During the feature extraction step, first the relationship between features is analysed by using correlation matrix. Correlation is frequently employed to assess whether a cause-and-effect relationship exists between two variables, with values ranging from -1 to 1. In the heatmap shown in Figure 2, the relationships between the features and the classification label are depicted. The correlation matrix in the image visualizes the relationships between different features in the dataset, as well as their correlation with the classification label. The color scale on the right shows how correlation values range from -0.2 (blue, indicating a negative correlation) to 1.0 (red, indicating a strong positive correlation). Many of the features, such as Prctile_90, Mean_val_abs, Svd, Mean, Median, Min, Max, and Sum, exhibit very high positive correlations (close to 1.0) with each other, suggesting strong linear relationships between these variables. Features like Std, Var, and Slope_sign_changes have weaker correlations with some other features but are generally well correlated with most variables. Interestingly, Skewness shows a very low or even negative correlation with the majority of the other features, indicating that it might capture a different aspect of the data. The Label column shows the correlation of the features with the classification label. Many features, such as Prctile_90, Mean_val_abs, and Svd, show a high positive correlation (~0.31), indicating that these variables are positively associated with the classification task and might be key contributors to the prediction process. In summary, this matrix highlights the interdependencies between features and their significance to the classification label, where several features show strong positive correlations, potentially indicating their importance in the model's performance.

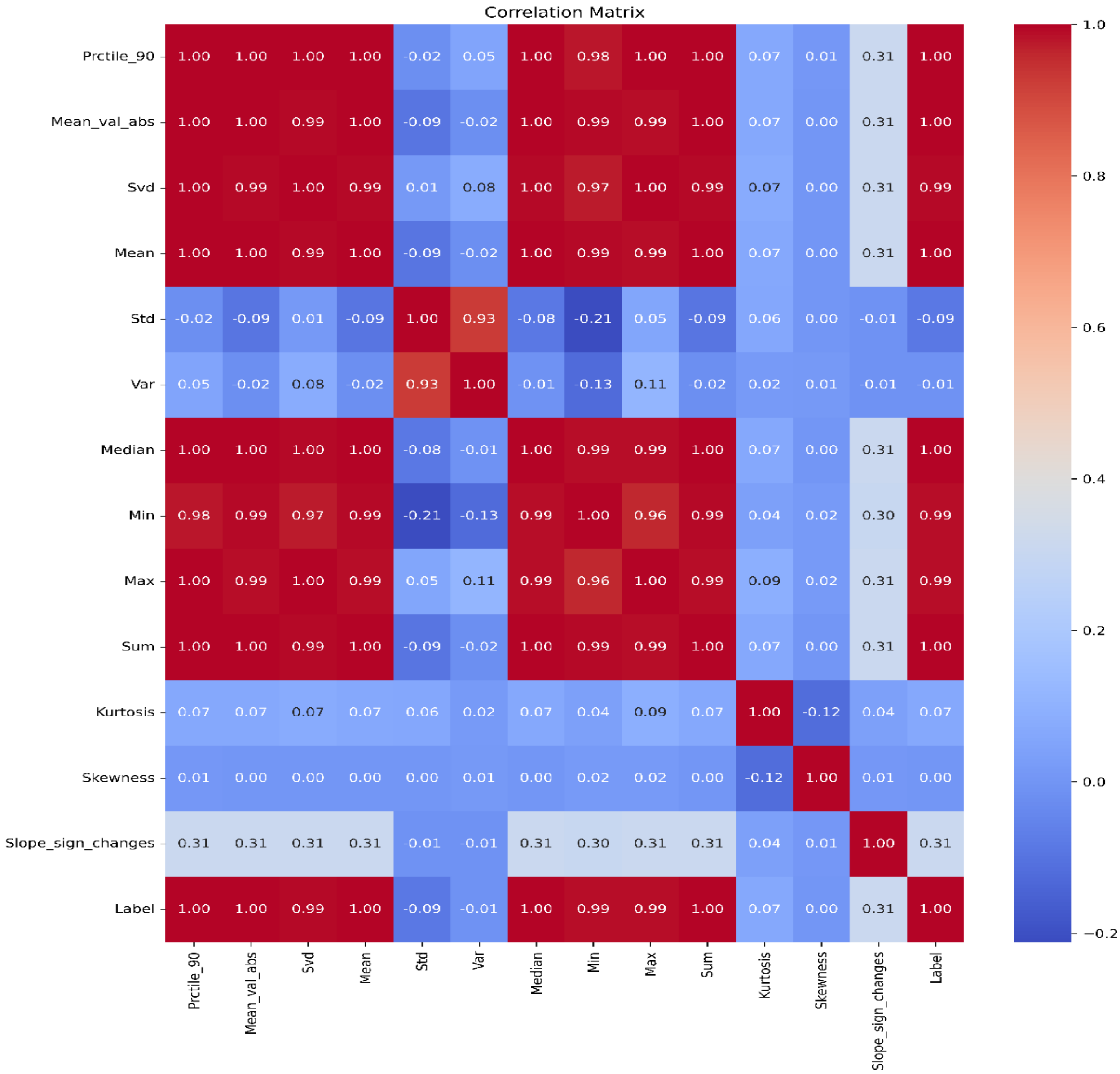

Figure 2. Features correlation matrix.

After the selection of the features, classification was performed as the final step. Table 1. presents the mean accuracy and standard deviation for used machine learning algorithms utilised in the classification task. Logistic regression achieved a mean accuracy of 0.9999 with a standard deviation of 0.0001, indicating high accuracy and minimal variability. Both the decision tree and random forest models reached a perfect mean accuracy of 1.0000, with a standard deviation of 0.0001, reflecting consistent performance across all evaluations. K-nearest neighbors (KNN) recorded a mean accuracy of 0.9999, demonstrating near-perfect performance with little variation. The support vector machine (SVM) and gradient boosting models both achieved a perfect accuracy of 1.0000, with a standard deviation of 0.0001, indicating robust and stable results. Overall, the algorithms displayed exceptionally high accuracy and consistency in the classification task, with very little variation between trials.

Table 1. Accuracy results for used algorithms.

Algorithms	Mean Accuracy	Standard Deviation
Logistic Regression	0.9999	0.0001
Decision Tree	1.0000	0.0001
Random Forest	1.0000	0.0001
KNN	0.9999	0.0001
SVM	1.0000	0.0001
Gradient Boosting	1.0000	0.0001

Table 2. presents the performance metrics (precision, recall, and F1-score) for the best classification algorithms, evaluated for two classes (schizophrenics and healthy subjects), along with overall accuracy and averages. The models achieve perfect classification performance across all metrics for both classes, with an accuracy of 100%.

Table 2. The best classification results.

	Precision	Recall	F1-score	Support
0	1.00	1.00	1.00	3170
1	1.00	1.00	1.00	2603
accuracy			1.00	5773
macro avg	1.00	1.00	1.00	5773
weighted avg	1.00	1.00	1.00	5773

Figure 3. shows the ROC curve and confusion matrix for the best classification algorithms. As it can be seen from the figure, the models demonstrate impeccable classification performance across all metrics for both classes, achieving an accuracy of 100%.

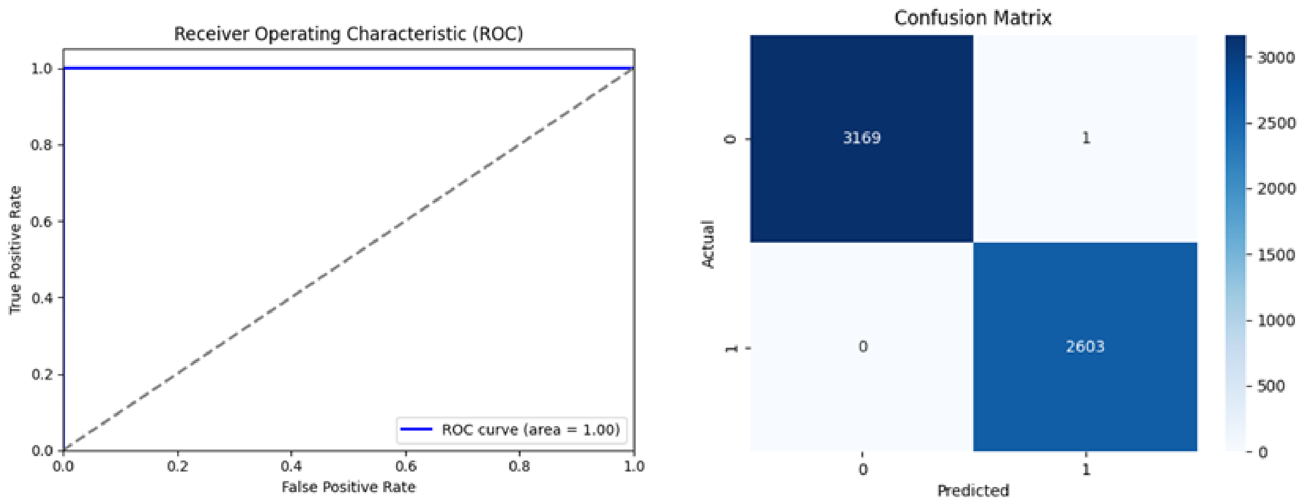

Figure 3. ROC curve and confusion matrix for best result.

The ROC curve and confusion matrix provide strong evidence that the model achieved excellent performance. The ROC curve, with an area under the curve (AUC) of 1.00, indicates perfect classification, demonstrating the model's ability to distinguish between positive and negative classes across all thresholds. Similarly, the confusion matrix shows that out of 5773 total samples, 3169 true negatives (TN) and 2603 true positives (TP) were correctly classified, with only one false positive (FP) and no false negatives (FN). This near-perfect performance highlights the model's effectiveness in accurately identifying both classes, a critical aspect in schizophrenia detection. Overfitting is typically characterized by a model performing well on training data but poorly on unseen data, which is not the case here, as both the ROC curve and confusion matrix reflect consistent and robust generalization. Moreover, the use of 5-fold cross-validation further reinforces the model's reliability by ensuring stable performance across multiple data splits. Together, these results confirm that the model generalizes well and achieves outstanding classification performance without any indication of overfitting.

The model comparison graph shows the accuracy distribution for six machine learning algorithms using 5-fold cross-validation. K-Nearest Neighbors (kNN) and Logistic Regression exhibit the lowest performance, with their accuracy distributions falling below those of the other models. The presence of a wider spread in kNN's results suggests greater variability across the folds, indicating that its performance may be less stable or sensitive to specific data splits. In comparison, Decision Tree, Random Forest, SVM, and Gradient Boosting achieve higher and more consistent accuracies, with most folds clustering around nearly perfect scores (close to 1.00). The absence of significant outliers in these models highlights their robustness and consistent generalization. The overall results suggest that tree-based models (Decision Tree, Random Forest, and Gradient Boosting) and SVM perform more effectively in this classification task, likely due to their ability to capture complex patterns in the EEG data.

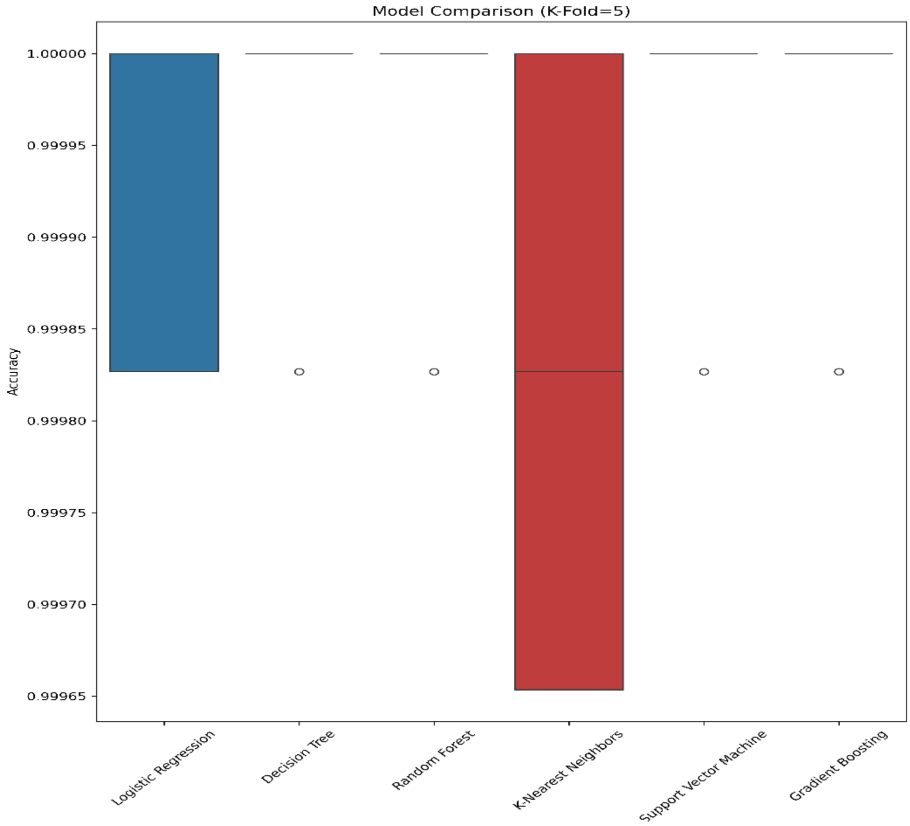

Figure 4. K-fold cross validation result.

4. CONCLUSIONS AND FUTURE WORK

This study applied six different machine learning algorithms for detecting schizophrenia (SZ) using multichannel EEG signals. The pre-processing of EEG data was followed by the implementation of 13 distinct feature extraction techniques, with the extracted features classified using various algorithms. Four of these algorithms—Decision Tree, Random Forest, Support Vector Machines (SVM), and Gradient Boosting—achieved classification accuracies of up to 1.00. Additionally, 5-fold cross-validation was employed to enhance the reliability of the results. The findings highlight the effectiveness of the proposed framework, demonstrating its potential for accurately detecting schizophrenia through EEG signals. Future research could explore the integration of more advanced deep learning techniques, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), for further improvement of classification accuracy. Additionally, expanding the dataset to include more diverse EEG recordings or investigating the use of transfer learning could enhance the model's generalizability. Incorporating real-time analysis of EEG signals for schizophrenia detection and extending the approach to other mental disorders are also promising directions for future work.

5. LIMITATIONS

Despite the promising results, this study has several potential limitations. First, the quality and size of the dataset could impact the generalizability of the findings. A small or imbalanced dataset might lead to biased model performance, while EEG signals are prone to noise and artifacts (e.g., muscle movements or eye blinks), which can affect feature extraction and classification reliability. Additionally, the study heavily relies on 13 feature extraction techniques, making it challenging to determine which features contribute most to detecting schizophrenia, and the use of complex models may limit interpretability. While 5-fold cross-validation enhances reliability, more robust techniques like stratified or nested cross-validation could further validate the results. Furthermore, the absence of external validation with independent datasets may limit the generalizability of the models to unseen data. Including deep learning approaches like CNNs or RNNs could provide additional insights, given their strength in time-series analysis. Lastly, translating these findings to real-world clinical settings remains challenging, as variations in EEG recording conditions and patient diversity may affect model performance, and computationally intensive algorithms may face limitations when deployed on portable or embedded devices. These limitations suggest avenues for future work and refinement to improve the robustness and applicability of the study's findings.

AUTHOR CONTRIBUTIONS

The authors contributed equally at every stage of the article.

CONFLICT OF INTEREST

There is no conflict of interest.

ETHICS

There is no ethical problem in the publication of this article.

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