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Research Article

Classification of Epileptic EEG Signals Using DWT-Based Feature Extraction and Machine Learning Methods

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ABSTRACT

Epileptic attacks can be caused by irregularities in the electrical activities of the brain. Electroencephalography (EEG) data demonstrating electrical activity in the brain play an important role in the diagnosis and classification of epileptic attacks and epilepsy disease. This study describes a method for detecting epileptic attacks using various machine learning methods and EEG features obtained with the Discrete Wavelet Transform (ADD). In the study, an EEG dataset consisting of five separate clusters from healthy and sick individuals was used, and the classification success between these conditions was examined separately. Support Vector Machine (SVM), Artificial Neural Networks (ANN), k-Nearest Neighbor (k-NN), Decision Trees (Tree), Random Forest, and Naive Bayes machine learning methods, which are widely used in classification, were used. In addition, comparisons were made with various windowing and overlap ratios. As a result, classification successes, as well as optimal windowing and overlap ratios were determined for various EEG clusters in the dataset.

1. Introduction

Epilepsy disease is defined as a serious chronic neurological disorder due to the disorder in the electrical activities of the brain, which can be detected by the analysis of the electrical signals produced by the brain neurons. Neurons in the brain are a complex interconnected structure that provides the communication function with organs and produces signals for communication. Electroencephalogram (EEG) and Electrocorticography (ECoG) methods are used to examine the signals produced by neurons. The signals obtained by EEG and ECoG are complex, noisy, and produce large amounts of data [1]. Identifying a function from these signals and identifying relevant information is difficult due to its nature. Therefore, removing the noise in the signals, defining the complex structure, and extracting the information about the function to be examined can be done with the help of machine learning without loss of performance. Diagnosis of related seizures in epilepsy disease can also be provided by EEG data machine learning methods. Researchers have conducted a series of studies using machine learning classifiers and statistical features to diagnose seizures in epilepsy [2].

Chen et al. studied the detection of EEG seizures by using Fourier properties of Doubletree Complex Wavelet Transform (DTCWT). In his work, he performed the wavelet transform up to 5 scales, and the method he proposed consists of only the fast Fourier transform. He stated that he achieved 100% classification accuracy with the method he proposed [3].

Acharya, et al., in their study, proposed a method for automatic detection of epilepsy using entropy. The proposed method is based on the extraction of entropy properties from EEG signals and the application of machine learning methods on these properties. In his work, the entropy extracted properties are Fuzzy Sugeno Classifier (FSC), Support Vector Machine (SVM), k-Nearest Neighbor (KNN), Probabilistic Neural Network (PNN), Decision Tree (DT), Gaussian Mixture Model (GMM), and Naive Bayes

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Classifier (NBC) using seven different classifiers and stated that they obtained the highest accuracy as 98.1% with the Fuzzy Classifier [4].

Raghu, et al., in their study, proposed the matrix determinant method as a new approach for the classification of epileptic seizures. Eleven classification problems were created between epileptic and non-epileptic EEG in order to examine the temporal dynamics in different states of epileptic activities. With the extracted features, they classified using Support Vector Machine (SVM), k-Nearest Neighbor (KNN), and Multilayer Perceptron (MLP) classifiers. They obtained 99.45% classification accuracy with their proposed method [5].

Li, et al., proposed a method using envelope analysis based on Discrete Wavelet Transform (DWT) and Neural Network Ensemble (NNE) for the classification of epilepsy EEG signals in their study. To obtain important features from the signals, they used the envelope analysis based on the discrete wavelet transform. They designed the ensemble model, called neural network ensemble, for epilepsy detection. They stated that they achieved a detection accuracy of 98.78% with their study [6].

Sikdar, et al., split the EEG signals into frequency sub-bands on a wavelet basis and applied fractal formalism to extract four different features as spectrum width, spectrum peak, spectrum skewness, and hurst exponent. In their study, they followed the effectiveness of the parameters in the extracted signals and found that there was no statistically significant difference between the sub-bands, but the groups differed significantly for band-limited EEG. They trained a Support Vector Machine (SVM) to classify the groups and achieved 99.6% accuracy for band-limited EEG [1].

Sharmila and Geethanjali performed split wavelet transform (DWT) analysis of EEG signals using linear and nonlinear classifiers and used this analysis to detect epileptic seizures. DWT-derived statistical properties of 14 different combinations of epilepsy detection were examined using Naive-Bayes (NB) and k-Nearest Neighbor (k-NN) classifiers. In their study, they stated that the Naive Bayes classifier performed better and showed 100% accuracy. In their analysis, they stated that the Naive Bayes classifier calculates faster than the k-nearest neighbor classifier and the Naive Bayes classifier would be more appropriate for the epileptic seizure detection system [7].

In their study, Ghassemi, et al. proposed a new scheme for the diagnosis of epileptic seizures in EEG signals using the tunable Q wavelet transform (TQWT) framework. They applied the proposed scheme to the Bonn dataset and analyzed the results. In their proposed method, they first split the signals into smaller windows and then applied a filter for noise. They used TQWT to separate the cleared signal into nine sub-bands. They extracted entropy-based and fractal dimension properties from each band they obtained and used collective learning methods AdaBoost, gradient boosting, and random forest to classify signals. As a result of the application, they stated that they achieved 99% accuracy with the hybrid method they proposed [8].

Aliyu, et al. proposed a recurrent neural network (RNN) method for the classification of epileptic EEG signals. They preprocessed the datasets with discrete wavelet transform (DWT) to filter out the noise in the signal and separate the features. They extracted 20 eigenvalue features to train and test the model. They compared their proposed method with logistic regression (LR), support vector machine (SVM), k-nearest neighbor (k-NN), random forest (RF), and decision tree (DT) methods. As a result of the study, they achieved the highest accuracy of 99% with 4 hidden layers in the model [9].

The aim of this study is to detect seizures in epilepsy disease beforehand by applying different machine learning methods on EEG signals. The methods presented and the results obtained will contribute to future studies on seizure detection and classification.

2. Material and Method

In this study, Support Vector Machine (SVM), Neural Networks, k-Nearest Neighbor (kNN), Decision Trees (Tree), Random Forest, and Naive Bayes machine learning methods, which are widely used for the classification of epileptic EEG signals, were used. The proposed method for the prediction of epileptic seizures consists of five different steps. In the first step, datasets of healthy, interictal, and ictal states were obtained from the EEG dataset in the UCI database. In order to examine different situations, sets were created with 0%, 25%, and 50% overlap on each dataset. Then, the 4th level wavelet coefficients were determined by Discrete Wavelet Transform (ADD) to obtain the features to be used in classification. The classification process was carried out by using the obtained features as input features for the machine learning classification algorithm. In the last stage, the decision-making process was carried out according to the results of the classification process. The flowchart describing these steps, in general, is shown in Figure 1.

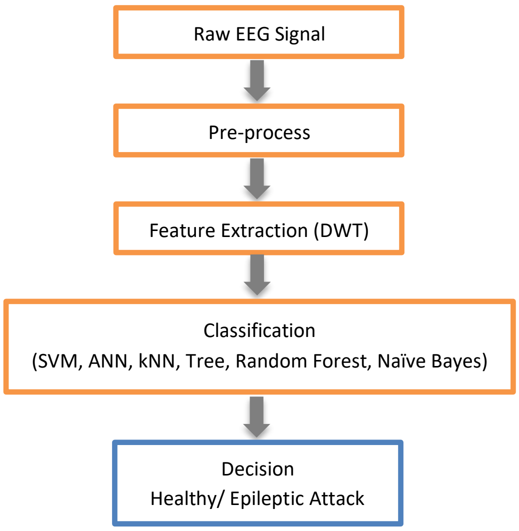

Figure 1. General flow chart of the proposed method

2.1. EEG Dataset

In this study, the open-access EEG dataset published by Andrzejak et al. was used [10]. This dataset includes the EEG signals of five healthy participants and five patients diagnosed with epilepsy and consists of five different parts (folder-set) (A-E). Each segment contains 100 single-channel EEG segments sampled at 173.61 Hz. Parts A and B consist of EEG recordings of healthy subjects. Part A indicates the state of being open, and part B indicates the state of being closed. C, D, and E parts are formed in the EEG signals of epileptic patients. C and D include EEG recordings from epilepsy patients in the epileptogenic zone during a seizure-free interval. Part E is the only set that contains signals during an epileptic seizure. A comparative description of parts of this dataset is given in Table 1.

In Figure 2, sample signs for the A, B, C, D and E parts of the dataset are given, respectively.

After the signals were converted with a 12-bit analog-to-digital converter, they were transferred to the computer environment. Since epileptic features manifest themselves in frequency bands below 30-40 Hz, a 0.53-40 Hz band-pass filter was applied to signals with a spectral range of 0.5-85 Hz [10, 11].

Table 1. Details of the EEG dataset

	Set A	**Set B**	**Set C**	**Set D**	**Set E**
Individuals	Healthy	Healthy	Epileptic	Epileptic	Epileptic
Situation	Eyes Open	Eyes Closed	Interictal	Interictal	Ictal
Electrode Type	Surface	Surface	Intracranial	Intracranial	Intracranial
Electrode Placement	International 10-20 System	International 10-20 System	Opposite the Epileptogenic Zone	Opposite the Epileptogenic Zone	Opposite the Epileptogenic Zone
Duration	23.6 sec	23.6 sec	23.6 sec	23.6 sec	23.6 sec

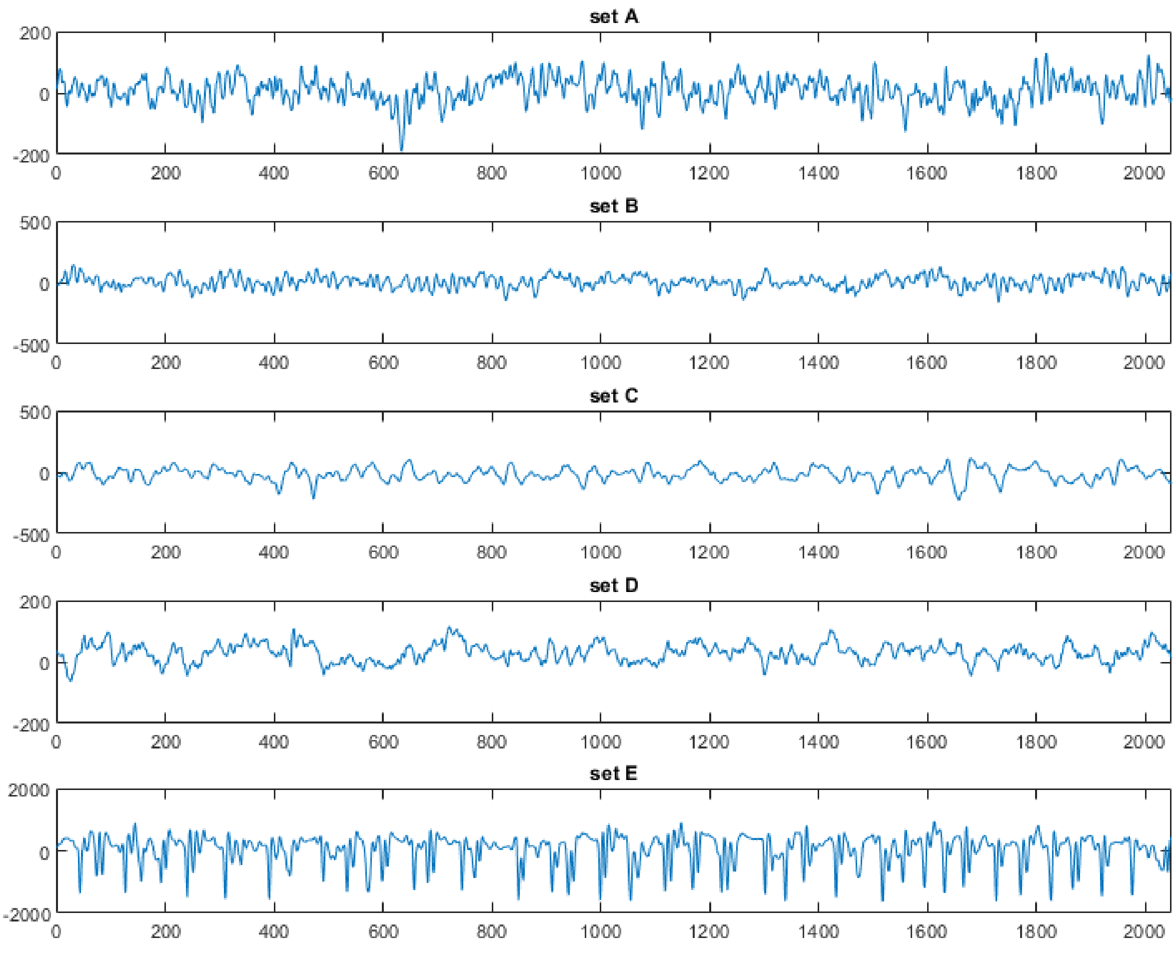

Figure 2. Signal samples from parts A, B, C, D and E

2.2. Discrete Wavelet Transform

Wavelet transform is a transformation type used for time-frequency analysis. It is a transformation technique that separates data into different frequency components and examines each component with its resolution at that scale. The wavelet transform of a signal as a function of time depends on the frequency and time variables. The most important advantage of DD is its window sizes ranging from narrow for high frequencies to wide for low frequencies. In this way, optimum time-frequency resolution can be achieved in all frequency ranges [3].

EEG signals are non-stationary signals. In the study, the obtained EEG signals were decomposed according to their frequency components using discrete wavelet transform and the features of the frequency bands at the decomposition levels were extracted. Since ADD uses a small window for high frequencies and a large window for low frequencies, it tries to provide the optimal resolution in terms of time and frequency [4].

A number of filters are used to analyze the input signals. With ADD, a high-pass filter is used to analyze the high-frequency components of the input signal and a low-pass filter is used to analyze the low-frequency components. The sampled outputs form the detailed D1 and approximate A1 sub-bands, respectively. A1 approach band diverges again, and this process continues as in Figure 3.

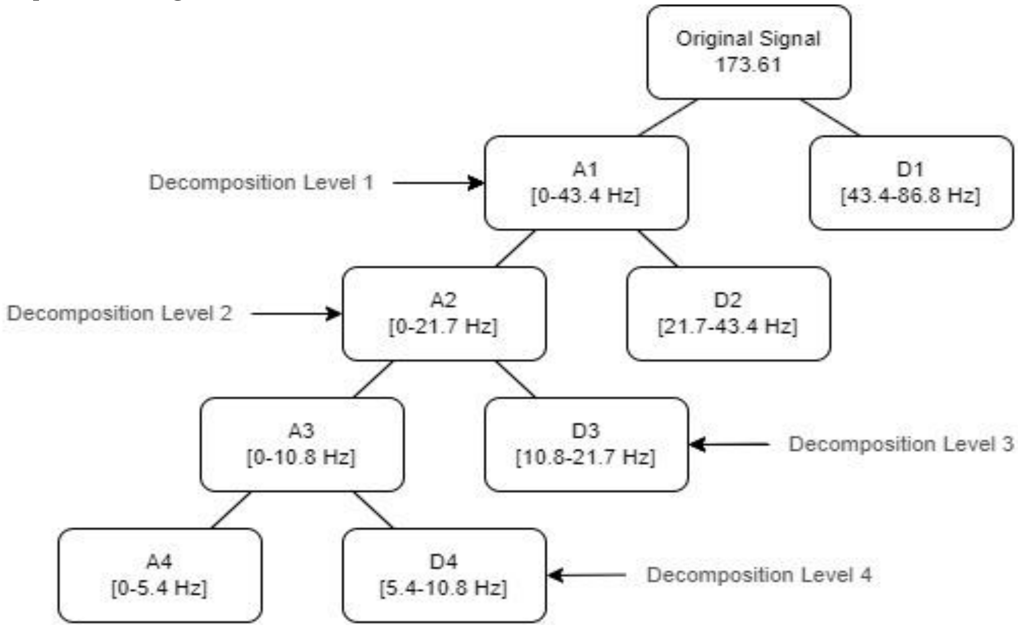

Figure 3. Flow chart for four-level DWT

As given in Table 2, EEG signals are divided into detailed sub-bands D1-D4 and finally sub-band A4 approximate. For the calculation of the wavelet coefficients for each segment, the 4th level ADD was applied by using the 2nd order Daubechies wavelet (db2).

Table 2. Range of frequency bands in wavelet decomposition

Sub-bands	**Frequency range (Hz)**
D1	43.4-86.8
D2	21.7-43.4
D3	10.8-21.7
D4	5.4-10.8
D5	0-5.4

Statistical features are applied to the set of wavelet coefficients in order to reduce the size of the feature vectors of the signals obtained by the DWT transform. To show the EEG signals' time-frequency distribution, the statistical features that used, are given below:

1. The absolute values of the coefficients in each sub-band are averaged.
2. The coefficients' standard deviation in each sub-band.
3. The skewness of each sub- bands' coefficients.
4. The kurtosis of each sub- bands' coefficients.
5. Calculation of the average of the coefficient strengths in each sub-band.
6. The ratio of surrounding sub-bands absolute mean values.
7. The absolute maximum of the coefficients' absolute values in each sub-band.
8. The absolute value of the coefficients in each sub-band that is the smallest.

Obtained feature vectors are used as input data for the classification of EEG signals. In total, 20 features were obtained for each segment.

2.3. Performance Evaluation

The success of a model that was created or a model that was already existing for the classification depends on all correct predictions collected from all predictions made. This method gives only the classification accuracy and that is usually not enough to determine the model quality. A complexity matrix is used to describe the prediction results of a classifier. A complexity matrix is a table often used to describe the performance of a classification model and has 4 parameters. These are named true positives, true negatives, false positives, and false negatives as shown in Table 3 [12].

Table 3. Confusion matrix

		Predicted	
		Positive	**Negative**
Actual	**Positive**	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

In this study, accuracy, sensitivity, specificity, precision, and F1-score ratios were used as performance measures. Mathematical expressions related to these performance measures are given in Equation 1, 2, 3, 4, 5, respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$Specificity = \frac{TN}{TN + FP} \quad (3)$$

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

$$F1 - Score = 2 * \frac{Sensitivity * Precision}{Sensitivity + Precision} \quad (5)$$

3. Experimental Study

There are many different classifiers in machine learning for inference from the signals of the dataset. The choice of classifiers may vary depending on the study and the required inference. In this study, the most widely used machine learning algorithms were used as classifiers. The dataset clusters are designated as A-E, AB-E, AB-CDE, and B-E. The AE cluster consists of the data of a healthy individual with eyes open and patients with epileptic attacks, the AB-E clusters of healthy individuals with eyes open and patients with epileptic attacks, the AB-CDE clusters of healthy individuals with eyes open and closed, and ictal and interictal data. epileptic patient data, BE cluster includes data of healthy individuals with eyes closed and patients who have epileptic attacks.

There is a supervised machine learning algorithm named Support Vector Machine (SVM) and this algorithm is usually used for solving regression and classification problems. Also called support vector network and non-probabilistic binary linear classification. SVM is used to sort data and group by model. Hyperplanes are used for classification. The data marked in the SVM needs to be trained [13]. In this study, 50 replication random sampling methods, cost (C) coefficient 1, and regression loss value (E) 0.1 were used for SVM.

Artificial neural networks are mathematical models based on the work of a nervous system that tries to replicate a decision-making process similar to human behavior. ANN becomes usable in daily business applications and gains acceptance for use in systems. Neural networks are less dependent on open coding. It is used to learn patterns and relationships in data rather than open coding. The mathematical formulations derived to mimic the nervous system are obtained after careful study of human behavior. Biological neurons are complex structures with limited understanding and have led to the development of different architectures in the past. Artificial neural networks consist of a series of artificial neurons. Each neuron functions as a basic computational unit that replicates an empty neuron. Artificial neural network applications try to imitate human ability depending on the given situation and conditions by learning from the events that occurred in the past and the application of these events to future tasks [14]. In this study, experiments were carried out at different training/test ratios by operating on 100 hidden layers as a neural network parameter.

The k-nearest neighbor classifier is a parametric and nonlinear classifier. This classifier is mostly used for large training sets. It is based on a measure of similarity between the training and test set. The n attributes are categorized according to the datasets. There is n-dimensional space pointed by each set, and the n-dimensional pattern space is formed by the training sets. A test dataset is assigned to the class based on k nearby training datasets [15]. For the k-nearest neighbor classifier, the number of neighbors is used as 5 in this study.

Naive Bayes is a probabilistic classifier based on Bayesian theory, with the assumption that each feature of a given class is independent of any other feature. The condition/specific absence estimation for the Naive Bayes model is based on maximum probability [16]. In this study, experiments were conducted for the Naive Bayes method with 50 repetitions of random sampling and different training/test ratios.

Random forest (RF) is a more powerful machine learning algorithm for classification. This model creates multiple decision trees and combines them to get a more accurate and stable forecast, providing greater accuracy. However, the performance of the RF classifier decreases when it is run with a high-dimensional training data set. Therefore, it cannot be said that this classifier is suitable for obtaining high accuracy results in large datasets [17]. For the random forest method, the number of trees was used as 15 in this study.

Decision tree (DC) is a supervised machine learning algorithm and is used in solving regression problems as well as classification. It uses a tree structure to represent the number of decisions. Returns a result by choosing the best decision based on entropy and information gain. The decision tree classifier is the most popular algorithm for identification and uncertainty applications [18]. The decision tree parameters in this study were used as the lowest number of samples in leaves 2 and the maturity level as 95%.

4. Results and Discussion

The data on the EEG dataset were first preprocessed in the MATLAB environment, and feature extraction was provided by using discrete wavelet transform and statistical features and they were turned into datasets suitable for classification. In order to determine the optimal windowing and overlap ratio, sets were created with 0%, 25%, and 50% overlap using 512, 1024, and 2048 windowing for each dataset. 36 separate datasets with feature extraction were defined as inputs for classification.

On each dataset created for the classification process, separate results were collected with a hold-out percentage of 25/75 by using SVM, ANN, k-NN, Tree, Random Forest, and Naive Bayes machine learning methods. The best windowing and overlap ratios were selected using 6 different classifiers in total.

Among all the results, choices between different windowing rates and hold-out rates for each class were made depending on the classification accuracy obtained. It was observed that the best values in terms of classification accuracy were obtained with a 25/75 hold-out ratio, 2048 windowing ratio, and 25% overlap. The results obtained from the filtered data, grouped according to the sets A-E, AB-E, AB-CDE, B-E are given in Table 4-7.

Table 4. Results of the models for the A-E dataset.

Classifier	Accuracy	Sensitivity	Specificity	Precision	F1-Score
k-NN	1.0000	1.0000	1.0000	1.0000	1.0000
Tree	0.9921	0.9921	0.9921	0.9921	0.9921
SVM	1.0000	1.0000	1.0000	1.0000	1.0000
Random Forest	0.9973	0.9973	0.9973	0.9973	0.9973
Neural Network	0.9985	0.9985	0.9985	0.9985	0.9985
Naive Bayes	0.9972	0.9972	0.9972	0.9972	0.9972

Table 5. Results of the models for the AB-E dataset.

Classifier	Accuracy	Sensitivity	Specificity	Precision	F1-Score
k-NN	1.0000	1.0000	1.0000	1.0000	1.0000
Tree	0.9921	0.9921	0.9921	0.9921	0.9921
SVM	1.0000	1.0000	1.0000	1.0000	1.0000
Random Forest	0.9973	0.9973	0.9973	0.9973	0.9973
Neural Network	0.9985	0.9985	0.9985	0.9985	0.9985
Naive Bayes	0.9972	0.9972	0.9972	0.9972	0.9972

Table 6. Results of the models for the AB-CDE dataset.

Classifier	Accuracy	Sensitivity	Specificity	Precision	F1-Score
k-NN	1.0000	1.0000	1.0000	1.0000	1.0000
Tree	0.9921	0.9921	0.9921	0.9921	0.9921
SVM	1.0000	1.0000	1.0000	1.0000	1.0000
Random Forest	0.9973	0.9973	0.9973	0.9973	0.9973
Neural Network	0.9985	0.9985	0.9985	0.9985	0.9985
Naive Bayes	0.9972	0.9972	0.9972	0.9972	0.9972

Table 7. Results of the models for the B-E dataset.

Classifier	Accuracy	Sensitivity	Specificity	Precision	F1-Score
k-NN	1.0000	1.0000	1.0000	1.0000	1.0000
Tree	0.9921	0.9921	0.9921	0.9921	0.9921
SVM	1.0000	1.0000	1.0000	1.0000	1.0000
Random Forest	0.9973	0.9973	0.9973	0.9973	0.9973
Neural Network	0.9985	0.9985	0.9985	0.9985	0.9985
Naive Bayes	0.9972	0.9972	0.9972	0.9972	0.9972

The classifiers were compared for each dataset set obtained. The comparison chart of the classifiers according to the sets is given in Figure 4.

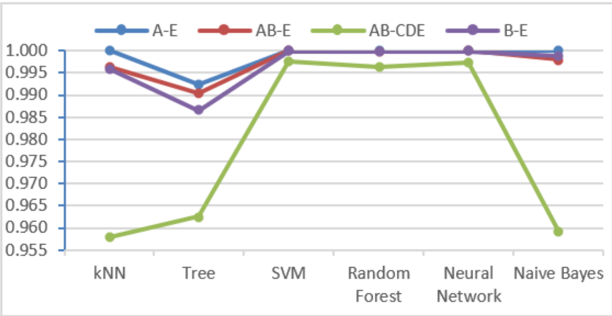

Figure 4. Comparison of classifiers in different datasets

In the study, it was observed that the highest accuracy result among the processed classifiers was obtained with SVM and k-NN in the A-E (healthy eyes people and epileptic patients) set. The results obtained in the study were compared with the results of the studies in the literature conducted with different classifiers on the same dataset. The data for the comparison are given in Table 9-12. According to the results in the literature, the results obtained in this study have higher accuracy performance than many studies.

Table 9. Comparison of the results obtained with the studies in the literature for the A-E dataset.

Method	Classifier	Performance %
Chandaka et al. [19]	SVM	99.00
Guo et al. [20]	ANN	96.00
Tzallas et al. [21]	Naive Bayes, ANN	99.00
Liang et al. [22]	ANN	99.00
This study	**k-NN, SVM**	**100.00**

Table 10. Comparison of the results obtained with the studies in the literature for the AB-E dataset.

Method	Classifier	Performance %
Jaiswal and Banka [23]	SVM	99.66
Tiwari et al. [24]	SpPCA+SVM	99.66
Acharya et al. [4]	Fourier Transform	99.33
Ramakrishnan. [25]	CNN	98.95
This study	**SVM**	**99.63**

Table 11. Comparison of the results obtained with the studies in the literature for the A-E dataset.

Method	Classifier	Performance %
Shoeb and Guttag [26]	SVM	96.00
Sairamya et al. [27]	kNN	99.30
Zeng et al. [28]	ANN	99.40
This study	**Random Forest**	**97.97**

Table 12. Comparison of the results obtained with the studies in the literature for the A-E dataset.

Method	Classifier	Performance %
Jaiswal and Banka [23]	SVM	99.50
Nicolaou and Georgiou [29]	SVM	82.88
Kumar et al. [30]	ANN, SVM	92.50
This study	**SVM**	**99.51**

It was observed that this study, which was carried out by using the features obtained by DWT and choosing the most appropriate windowing and overlap ratio, classified the healthy and epileptic patient data on different sets with better performance when compared to the results in the literature. It is thought that the proposed method can be a useful tool in the decision-making process in medical diagnosis systems. In addition, the method can be further developed by using different EEG clusters and different classification techniques together.

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