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Research Article

Comparison of Machine Learning Algorithms in the Detection of Alzheimer's Disease

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Abstract

Alzheimer's disease is a neurodegenerative disorder that causes loss of cognitive function and cognitive decline in individuals. Detection of the disease at an early stage is important to slow down the devastating effects of the disease. The use of an autonomous computerized support system that can assist specialist physicians in the diagnostic process saves time and helps reduce human error. For this reason, a high-accuracy classification study was aimed at utilizing different machine learning algorithms for early diagnosis of Alzheimer's disease. Within the scope of this study, an open source data set created with Electroencephalogram (EEG) signals from 24 healthy and 24 Alzheimer's patient volunteers was used. 28 features, including spectral and statistical features, were extracted from each channel of the EEG signals. The extracted features were evaluated to the feature importance algorithm and the five most significant features that could distinguish between Alzheimer's individuals and healthy individuals were determined. Four machine learning algorithms are trained with the determined features. 70% of the data was used for training and the algorithms were trained with a 10-fold cross-validation method. When the four machine learning algorithms were tested with the data reserved for testing, which the algorithms had not seen before, the highest accuracy was obtained with the Gradient Boosting Classifier (GBC) algorithm with 96.43%.

Keywords: Alzheimer, EEG, Feature Extraction, Feature Selection, Gradient Boosting Classifier, Machine Learning.

Alzheimer Hastalığının Belirlenmesinde Makine Öğrenmesi Algoritmalarının Karşılaştırılması

Öz

Alzheimer hastalığı, bireylerde bilişsel fonksiyon kaybı ve bilişsel gerilemeye neden olan nörodejeneratif bir rahatsızlıktır. Hastalığın erken evrede tespit edilmesi hastalığın yıkıcı etkilerini yavaşlatmak için önem arz etmektedir. Uzman doktorlara teşhis sürecinde yardımcı olabilecek otonom bir bilgisayarlı bir destek sisteminin kullanılması zamandan tasarruf sağlayarak insan hatasının azaltılmasına yardımcı olur. Bu nedenle, Alzheimer hastalığının erken teşhisi için makine öğrenmesi algoritmalarından yararlanılarak yüksek doğruluklu bir sınıflandırma çalışması hedeflenmiştir. Bu çalışma kapsamında, 24 adet sağlıklı ve 24 adet Alzheimer hastası gönüllüden alınan Elektroensefalogram (EEG) sinyalleri ile oluşturulmuş açık kaynak olarak sunulan bir veri setinden yararlanılmıştır. EEG sinyallerinin her bir kanalından spektral ve istatistiksel öznitelikler olmak üzere 28 öznitelik çıkartılmıştır. Çıkartılan öznitelikler, karar ağacı öznitelik önem algoritmasına uygulanmış ve Alzheimer bireyler ile sağlıklı bireyleri ayırt edebilecek en anlamlı 5 öznitelik belirlenmiştir. Belirlenen öznitelikler ile dört makine öğrenmesi algoritması eğitilmiştir. Eğitim için verilerin %70'i kullanılmış ve algoritmalar 10-kat çapraz doğrulama yöntemi ile eğitilmiştir. Daha önce algoritmaların görmediği, test için ayrılan veriler ile makine öğrenmesi algoritmaları test edildiğinde en yüksek doğruluk % 96.43 ile Gradient Boosting Sınıflandırıcısı (GBC) algoritması ile elde edilmiştir.

Anahtar Kelimeler: Alzeimer, EEG, Feature Extraction, Feature Selection, Gradient Boosting Sınıflandırıcısı, Makine Öğrenmesi.

1. Introduction

Alzheimer's disease is a common type of dementia that affects the central nervous system and causes widespread intracellular degeneration (Elgendi et al., 2011). The disease limits daily living skills and in later cases makes individuals completely dependent on someone (Poza et al., 2007). Every year, thousands of people get Alzheimer's disease and it is late for the disease. However, when Alzheimer's disease is detected, it is possible to slow down the disease and reduce its destructive effects (Riemenschneider et al., 2002). Currently, there is no widespread method for early diagnosis. For this reason, methods for detecting Alzheimer's disease with Electroencephalogram (EEG) signals are being tried (Ahmadlou et al., 2011; Elgandelwar & Bairagi, 2021), since it directly transmits the synaptic activity of the brain (Michel et al., 2009), is easier to use and more affordable than most methods (Foxe & Snyder, 2011; Luu et al., 2001).

There are three features typically addressed in studies to detect Alzheimer's disease from EEG signals. These features are slowdown, reduced complexity, and loss of synchronization. (Babiloni et al., 2016; Benz et al., 2014). To investigate these effects, researchers extracted multiple features from EEG signals. Research has been done on spectral features for slowing down (Bairagi, 2018), entropy features for complexity (Şeker et al., 2021) and coherence features for synchronization (Meghdadi et al., 2021).

Extracted features have been tested with different machine learning and deep learning algorithms. Alzheimer's and healthy individuals were classified using different classification techniques. In one of these studies (Fiscon et al., 2018), healthy, Alzheimer's and mild cognitive impairment were tried to be classified among themselves by using the features extracted by the wavelet method. In the study, healthy volunteers and Alzheimer's patients were classified with the decision tree method with 83% accuracy. In another recent study, the CNN algorithm was used to classify healthy volunteers and Alzheimer's disease, and the two classes could be distinguished with an accuracy of 92.29% (Meghdadi et al., 2021).

In this paper, the aim of the research study is to detect Alzheimer's disease with high accuracy with EEG signals and help the diagnosis of the disease. In order to diagnose Alzheimer's, patients and healthy individuals were classified by extracting spectral and statistical features from EEG signals. The proposed features were compared with four different classification methods and the performance of the algorithms was evaluated. As can be seen, although different classifiers and different features are used in studies in the literature, the main purpose is to distinguish between the EEG signals of Alzheimer's patients and healthy individuals. Considering these studies, our study was able to distinguish two classes with a higher rate of 94.34% than other studies in the literature.

The remainder of this article is structured as follows. Part II discusses dataset, spectral and statistical feature extraction, feature selection and classification algorithms under the heading of material and method. Part III contains the results and discussion. Finally, conclusions and recommendations are given in Part IV.

2. Material and Method

In the material and method section, the data set used in the study, spectral and statistical feature extraction from EEG data, selection of features and classification algorithms used are mentioned. The general workflow of the classification study is given in Figure 1.

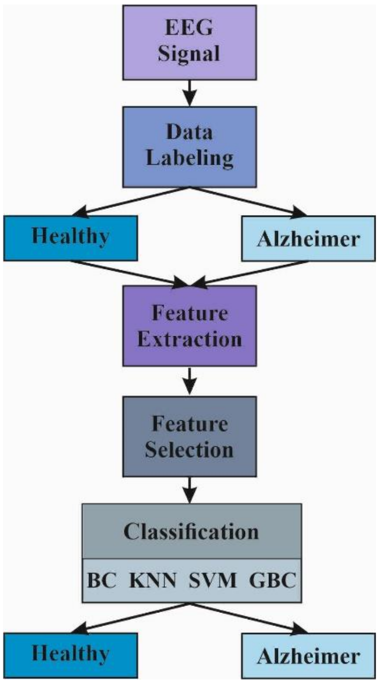

Figure 1. The general work flow of the classification study.

2.1. EEG Dataset

The EEG dataset used in this study is an open source dataset (Pineda et al., 2020). A 10-20 electrode system and 19 electrodes were used to collect EEG data. The device's sampling frequency is 128 Hz, and each volunteer was recorded for 8 seconds. The records are named A, B, C, and D. While the EEGs of the volunteers in groups A and C were recorded while their eyes were open, the EEGs of the volunteers in groups B and D were recorded while their eyes were closed. Groups A and B consisted of 24 volunteers with an average age of 72 who did not suffer from neurological disorders. C and D consisted of 24 Alzheimer's patients with an average age of 69 years.

2.2. Feature Extraction

Within the scope of the study, 28 spectral and statistical features from each channel of EEG data were extracted. To extract spectral features Welch method (Şahin Sadık et al., 2022) were utilized to calculate the power spectral densities (PSD) of the EEG sub-bands (delta, theta, alpha, beta). Further, with calculated PSDs, these spectral features were extracted:

- PSDs of the each sub-band
  $PSD_i,\ i \in \{delta, theta, alfa, beta\}$
- Relative powers of each sub-band
  $PSD_i \,/\, PSD_{total},\ i \in \{delta, theta, alfa, beta\}$
- Spectral power ratios between sub-bands
  $PSD_i \,/\, PSD_j,\ \ (i, j) \in \{delta, theta, alfa, beta\},\ i \neq j$

Further, the extracted statistical features are standard deviation, mean, skewness, kurtosis, maximum, minimum, variance and median.

2.3. Feature Selection

Decision tree feature importance method (Al Iqbal et al., 2012) was applied to the extracted attributes and a importance value was determined for each attribute. The most significant features were determined as theta band power to delta band power ratio, theta band power to beta band power ratio, mean, standard deviation and kurtosis. The bar chart graph of the decision tree feature importance algorithm is given in Figure 2.

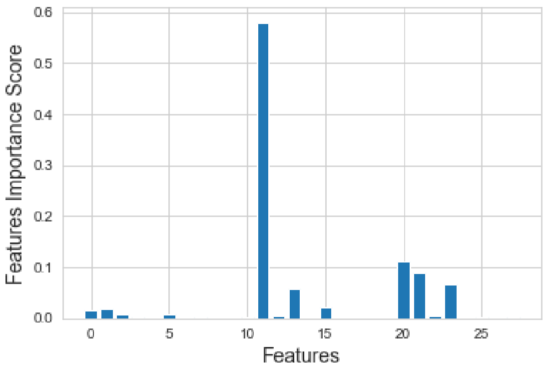

Figure 2. Bar chart of decision tree regressor feature Importance scores.

2.4.Classification Algorithms

In this study, features extracted from EEG signals of healthy and Alzheimer's individuals were classified using four different classification algorithms and their performances were compared. These classification algorithms used in this study are explained briefly below.

Bagging Classifier (BC) Algorithm is a technique first proposed by L. Breiman (Breiman, 1996). While making the classification, the existing training set is used and new training sets are derived. It is aimed to retrain the basic student. Using the substitution technique, a training set with n samples is randomly generated using n samples in the training set. The selected samples are put into the training set. In this algorithm, some examples may not be included in the training set, while some examples may be included more than once.

The K-nearest neighbor (KNN) algorithm was first developed in 1967. KNN algorithm which is a supervised, sample-based machine learning algorithm, is efficacious for both classification and regression problems. (Cover & Hart, 1967). If the user has a little knowledge on the distribution of the data, the KNN algorithm may be the most suitable machine learning solution. The KNN algorithm is mathematically quite simple compared to other algorithms. It can determine the class of test data according to the positions of the training data in the sample space (Chakrabarti et al., 2008; Mitchell & Mitchell, 1997). For this, it uses the Euclidean distance relation mathematically.

The Support Vector Machine (SVM) is the second supervised machine learning algorithm used in this study. It has the ability to divide data into two or more classes in two-dimensional space, three-dimensional space and multi-dimensional space. The data could be separated linearly when the data set could be separated by a straight line. A is used to separate points placed on a plane and this line is required to be at the maximum distance for points belonging to two classes (Cortes & Vapnik, 1995; Pedregosa et al., 2011)

Gradient Boosting Classifier (GBC) is a machine learning algorithm that is used for both regression and classification problems (Bauer & Kohavi, 1999). GBC proceeds by building an additive model. It elevates the learner by combining weak learners for a learner. They are basic learner regression trees. It moves over the error calculated in the previous tree.

3. Results and Discussion

While evaluating the data within the scope of the study, spectral and statistical features were extracted from each channel of the EEGs of both Alzheimer's patients and volunteers without any neurological disorders. When the extracted 28 features were evaluated by the feature importance selection algorithm, the most significant features were determined as theta band power to delta band power ratio, theta band power to beta band power ratio, mean, standard deviation and kurtosis. ten-fold cross-validation was applied to the data and 30% of the data was reserved for testing and 70% for training. Four classification algorithms were trained with training data and tested with test data. In Figure 3, classification results of the BC, KNN, SVM and GBC algorithms are given with 10-fold cross-validation.

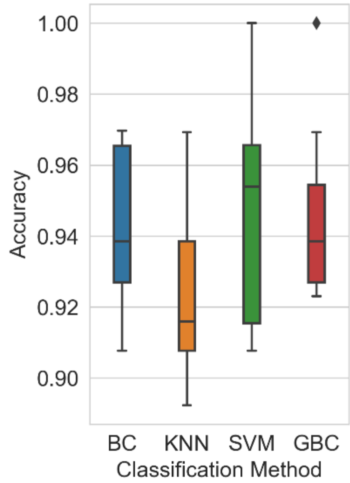

Figure 3. All classification algorithms had ten-fold cross-validation results. BC, KNN, SVM, GBC.

When the training results were evaluated, the accuracy was 94.31% (±0.021) with BC, 92.47% (±0.023) with KNN, 94.77% (±0.031) with SVM, and 94.62% (±0.023) with GBC. When the system was tested with 30% separated test data, the test accuracies given in Table 1 were obtained. When the test accuracies were examined, 95.71% with BC, 96.07% with KNN, 95.36% with SVM and 96.43% with GBC were obtained. In addition, the performance of classification algorithms has been tested with precision, recall and f1-score.

Table 1. Performance metrics for all classification algorithms.

Method	Accuracy (%)	Precision	Recall	F1-Score
BC	95.71	0.96	0.96	0.96
KNN	96.07	0.96	0.96	0.96
SVM	95.36	0.95	0.95	0.95
GBC	**96.43**	**0.96**	**0.96**	**0.96**

Equation 1, Equation 2, Equation 3 and Equation 4 are accuracy recall, f1 score and precision parameters respectively, which are performance metrics and whose values are given in Table 1.

$$Accuracy = \frac{P_T+N_T}{P_T+N_T+P_F+N_F}\times 100 \quad (1)$$

$$\text{Recall}=\frac{P_T}{P_T+N_T}\times 100 \quad (2)$$

$$\text{Precision}=\frac{P_T}{P_T+P_F}\times 100 \quad (3)$$

$$\text{F1-score}=\frac{2\times\text{Recall}\times\text{Precision}}{\text{Recall}+\text{Precision}}\times 100 \quad (4)$$

P_T is true positives, N_T demonstrate true negatives, P_F is false positives and N_F demonstrates false negatives (Equation 1,2 and 3). The F1 score expression, on the other hand, is obtained by multiplying the recall and precision values twice, dividing by the recall and precision values, and is expressed as a percentage. The results of the GBC algorithm, which gives the highest test accuracy, are shown in the confusion matrix in Figure 4. Here, 117 of 123 healthy volunteers were guessed correctly, while 6 of them were wrongly guessed. Out of 159 Alzheimer's volunteers, 153 were predicted correctly, while 4 were predicted incorrectly.

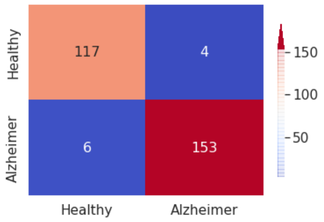

Figure 4.Confusion matrix for GBC test results.

3. Conclusions and Recommendations

With this study, 28 features, including spectral and statistical features, were extracted from the EEG signals of Alzheimer's patients and volunteers without a neurological disorder in a data set presented as open source. All features were evaluated by the decision tree feature importance algorithm to find the most significant features. The most significant features; Theta band power to delta band power ratio, theta band power to beta band power ratio were determined as mean, standard deviation and kurtosis. The selected features are divided into 70% training and 30% testing. The training dataset and the ten-fold cross-validation technique were used to train the BC, KNN, SVM, and GBC algorithms. Then, system performance was tested with 30% test data set. While data can be classified with an accuracy of 95.71% with BC, classification is made with an accuracy of 96.07% with KNN. Classification was made with SVM with an accuracy of 95.36%. The highest accuracy was found with the GBC algorithm with a rate of 96.43%.

With our proposed study, Alzheimer's and healthy individuals could be distinguished from EEG signals with higher accuracy compared to other studies in the literature. In future studies, system performance can be tested with other open-source datasets. Furthermore, the proposed system can be used as a computer-aided diagnostic system to assist physicians in developing simultaneously.

5. Acknowledge

Part of the results of this study was presented as a summary paper at the 2nd International Conference On Engineering And Applied Natural Sciences (ICEANS) 15-18 October 2022.

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