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DETECTION OF ALZHEIMER'S DISEASE FROM ELECTROENCEPHALOGRAPHY (EEG) SIGNALS USING MULTITAPER AND ENSEMBLE LEARNING METHODS

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Abstract: Alzheimer's disease is a complex brain disease and is also the most common form of dementia that leads to impaired social and intellectual abilities. The disease only manifests itself with a simple forgetfulness, as the disease progresses, the patient forgets the recent events, cannot recognize his family members and close environment, and becomes in need of care in the last stage. Early detection is therefore crucial for medical intervention to prevent brain injury and prolong everyday functioning. In this study is aimed to detection of Alzheimer's disease from EEG signals using the multitaper and ensemble learning methods. The dataset comprises of 24 healthy people and 24 Alzheimer's patients' EEG signals. 49 features were extracted by calculating the power spectral density (PSD) of the frequencies of the EEG signals between 1-49 Hz using the multitaper method. Then, the performances of AdaboostM1, Total Boost, Gentle Boost, Logit Boost, Robust Boost, and Bagging ensemble learning algorithms were compared. As a result of experiments, the Logit Boost algorithm has the highest performance. The algorithm has achieved a promising performance of 93.04% accuracy, 93.09% f1-score, 92.75% sensitivity, 93.43% precision, and 93.33% specificity.

Keywords: Ensemble learning, Signal processing, EEG, Multitaper, Alzheimer 's Disease

Multitaper ve Topluluk Öğrenme Yöntemlerinin Kullanılarak Elektroensefalografi (EEG) Sinyallerinden Alzheimer Hastalığının Tespiti

Öz: Alzheimer hastalığı karmaşık bir beyin hastalığıdır, aynı zamanda sosyal ve entelektüel yeteneklerde bozulmaya yol açan demansın en yaygın şeklidir. Hastalık sadece basit bir unutkanlıkla kendini gösterir, hastalık ilerledikçe hasta son olayları unutur, ailesini ve yakın çevresini tanıyamaz, son aşamada bakıma muhtaç hale gelir. Bu nedenle erken teşhis, beyin hasarını azaltmak ve günlük işleyişi daha uzun süre korumak için tıbbi müdahalede önemli bir rol oynamaktadır. Bu çalışmada, multitaper ve topluluk öğrenme yöntemleri kullanılarak, EEG sinyallerinden Alzheimer hastalığının tespitinin yapılması amaçlanmıştır. Veriseti 24 sağlıklı bireyden ve 24 Alzheimer hastasından kaydedilen EEG sinyallerinden oluşmaktadır. EEG sinyallerinin 1-49 Hz arasındaki frekanslarının güç spektral yoğunluğu (PSD) multitaper yöntemi kullanılarak hesaplanarak, 49 öznitelik çıkarıldı. Daha sonra AdaboostM1, Total Boost, Gentle Boost, Logit Boost, Robust Boost ve Bagging topluluk öğrenme algoritmalarının performansları karşılaştırıldı. Deneyler sonucunda, Logit Boost algoritması en yüksek performansa sahipti. Algoritma, %93,04 doğruluk, %93,09 f1-skor, %92,75 duyarlılık, %93,43 kesinlik ve %93,33 özgüllük ile umut verici bir performans elde etti.

Anahtar Kelimeler: Topluluk öğrenme, Sinyal işleme, EEG, Multitaper, Alzheimer hastalığı

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1. INTRODUCTION

Alzheimer's disease (AD) is the most prevalent type of dementia that primarily affects elderly people and is defined by the breakdown of brain tissue, leading to impaired social and intellectual abilities (Smailovic and Jelic, 2019). The World Health Organization estimates that more than 55 million individuals worldwide suffer from dementia, and there are about 10 million new cases each year. AD can contribute to 60-70% of cases (World Health Organization, 2021). AD patients have memory loss, mood, personality changes, and cognitive impairments such as affecting their ability to move, speak, and complete familiar tasks like doing their normal daily activities (Cai and Jeong, 2020; Guo et al., 2020).

AD does not have a reliable diagnosis and effective treatment yet. The diagnosis is fairly challenging, and it is usually made by excluding other potential causes of dementia symptoms (Blennow, 2010). The progression of AD can be categorized into four stages. Mild cognitive impairment is referred to as the initial stage. There is typically some memory loss. Maintains abilities in other cognitive areas and functional activities. Some mild cognitive disorder patients (6 - 25%) progress to AD. Increased cognitive deficits characterize the following stage. The second and third stages are called mild AD and moderate AD, while the final stage is called severe AD; it totally depends on the caregivers. Mild and moderate AD are vital stages, because early diagnosis of AD can be made at these stages and has proven beneficial as medications work at this stage. In the final stage of the AD, the patient cannot be cured and therefore can lead to death (Bairagi, 2018). It causes death on average eight years after the diagnosis of AD. Therefore, early diagnosis is crucial in medical intervention to maintain daily functioning longer, reduce brain damage, and give the patient time to make plans for the future (Rodrigues et al., 2021).

Different neuroimaging techniques, namely positron emission tomography (PET), EEG, magnetic resonance imaging (MRI), and single photon emission computed tomography (SPECT) are used for the diagnosis of AD (Kulkarni, 2018). EEG records electrical waves produced by nerve cells in the brain. EEG offers superior millisecond-level temporal resolution in comparison to other neuroimaging techniques. Recording the EEG at rest is advantageous when examining AD patients as it requires little cooperation and is not stressful (Klepl et al., 2021). In addition, EEG is a relatively easy, inexpensive and widely available, portable and noninvasive method. Because of these advantages, EEG is more preferred (Tosun, 2021).

Early diagnosis of diseases by EEG provides an opportunity for early treatment. It is therefore particularly promising. In the relevant literature, there are limited studies investigating the connection between EEG signals and Alzheimer's diagnosis. Amezquita-Sanchez et al. (2019) suggested a model for AD and mild cognitive impairment classification tasks. They used enhanced probabilistic neural network (EPNN) to automatic classify and MUSIC-EWT algorithm to decompose the EEG signals. The accuracy of the model is 90.3%. Aslan (2022) developed a computer diagnostic system for automatic detection of AD using the same EEG dataset. After applying wavelet transform to the data received from each channel, statistical properties were calculated. With the k-nearest neighbor (kNN) classifier, healthy and AD groups were distinguished with an accuracy of 91.12%. Fiscon et al. (2018) combined EEG signal processing with supervised methods for classification of Alzheimer's patients. The EEG dataset consists of 49 AD and 23 healthy subjects. They performed a time-frequency analysis by applying both Wavelet and the Fourier Transforms. An accuracy value was 83.3% in distinguishing AD and control groups. Amini et al. (2021) used convolutional neural network (CNN), linear discriminant analysis (LDA), kNN, and support vector machine (SVM) approaches in diagnosis of AD using EEG signal. Using CNN approach, the accuracy of AD was 89.1% and the accuracy of the healthy population was 75%. Early diagnosis and treatment can slow down the progression of the disease. Therefore, there is a need to develop easy and applicable methods and it is of critical importance.

We proposed an ensemble learning model that used the multitaper feature extraction method and the ensemble learning classification methods to accurately distinguish Alzheimer patients and healthy person. The main contributions of this study are summarized as below:

a. An automatic classification model, which efficiently combines multitaper feature extraction and ensemble learning methods, was used for detection of AD from EEG signals.

b. Since modified periodograms produced from a succession of mutually orthogonal windows or tapping were averaged to produce a reliable estimate of PSD in the study, the multitaper method reduced prediction bias and prevented data loss.

c. The ensemble learning methods, namely AdaboostM1, Total Boost, Gentle Boost, Logit Boost, Robust Boost, and Bagging, were compared to discover the best performance.

2. MATERIAL AND METHOD

2.1. Proposed Method

In the study, an EEG-based ensemble learning model was proposed for automatic detection of AD. 49 features were extracted by calculating the PSD values of the frequencies between 1-49 Hz of the EEG signals with the multitaper spectral analysis method. Using these 49 features, ensemble learning algorithms were performed in the classification of EEG-based AD and the performances of the algorithms were compared. The implementation stages of the proposed ensemble learning model are given in Figure 1:

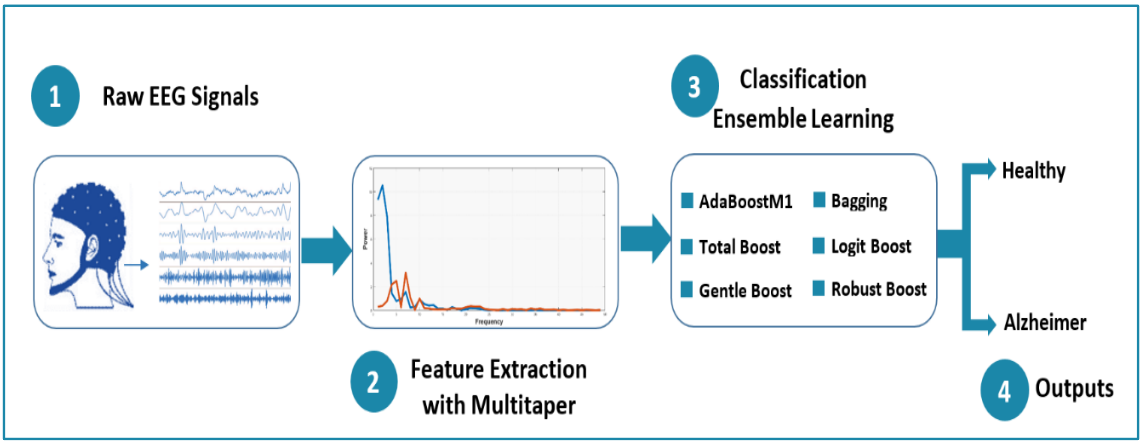

Figure 1:
The Implementation Stages of the Proposed Ensemble Learning Model

2.2. Dataset

In this study, EEG signals recorded by Florida State University researchers from 48 subjects (24 Alzheimer's and 24 Healthy) were used. The EEG dataset is publicly available (Pineda et al., 2020). EEG signals were recorded from the 19 (Fp1, Fp2, Fz, F3, F4, F7, F8, Cz, C3, C4, T3, T4, Pz, P3, P4, T5, T6, O1, and O2) with a Biologic Systems Brain Atlas III Plus workstation labelled in accordance with an international 10–20 system at 128 Hz sampling rate. EEG recordings comprise of A, B, C, and D groups. Groups A and B comprise of 24 healthy elderly people comprise of negative for any psychiatric disorder or all disorder. Groups C and D comprise of 24 AD patients diagnosed through the "National Institute of Neurological and Communicative Disorders and Stroke and the Alzheimer's Disease and Related Disorders Association", and "Diagnostic and Statistical Manual of Mental Disorders" criteria (Pineda et al., 2020). Figure 2 shows the 10-20 electrode layout.

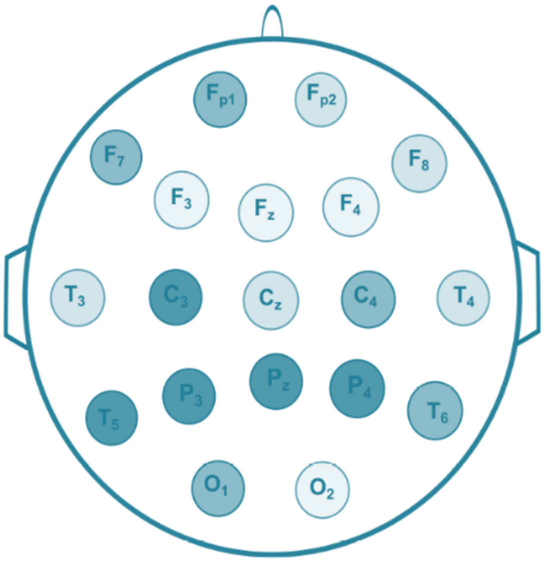

Figure 2:
Electrodes Positioning for the International 10-20 System

2.3. Feature Extraction with Multitaper Method

Feature extraction is a dimensionality reduction process in which raw data is reduced to numerical features that can be processed while preserving the information in the original dataset (Zebari et al., 2020). Large datasets contain many variables and require a lot of computing resources to process these datasets. Feature extraction are methods that select variables and/or combine them into features, effectively reducing the amount of data that needs to be processed, and still completely and accurately describe the original dataset (Balan and Sunny, 2018). It not only reduces the search space by reducing the size, but also improves the classification quality by reducing the processing complexity (Özmen et al, 2017). In this study, the multitaper method was used to calculate the PSD values of the frequencies between 1-49 Hz of the EEG signals, and 49 features were extracted. The mathematical foundations of this method are presented in 2.3.1.

2.3.1. Multitaper Method

The multitaper method is one of a number of widely used approaches for PSD estimation, and improves spectrum estimation by addressing of spectral leakage and its variance. M tapers are utilized and each one is slightly different, thus reducing energy leakage between frequencies (Upadhya et al., 2018). Multitaper method is calculated by equation 1 (Thomson and Vernon, 1998; Güneç et al., 2021):

$$\vartheta_{(\mathrm{w})} = \left| \sum_{n=1}^{K} h_{K-n} y(n) e^{-j\omega n} \right|^2 \qquad (1)$$

With the use of a number of mutually orthogonal windows or tapers in order to reduce the variability in the periodogram and so create a consistent estimate of the PSD, the multitaper method averages modified periodograms. The tapers exhibit optimal time-frequency concentration characteristics in addition to mutual orthogonality. The effectiveness of the multitaper method depends on the tapers' orthogonality and time-frequency concentration (Candy, 2019).

2.4. Classification with Ensemble Learning

The ensemble learning model combines various machine learning classifiers to produce a better-performing outcome. The model is effective in reducing high variance and also contributes to improved performance by reducing bias (Dong et al., 2020). In the traditional classification method, many individual classification algorithms such as Naive Bayes, SVM or kNN are used to build the classification model on a prelabeled dataset. The individual classification algorithm may have some weaknesses in a given condition in the classification task (Matloob et al., 2021). Therefore, ensemble learning model was performed so that the strengths of multiple classification algorithms could be combined to provide better classification in the dataset. The widely-used ensemble learning methods include bagging and boosting.

2.4.1. Boosting

Boosting takes the base learning methods repeatedly while varying the distributions or weightings of the training data. The boosting algorithm operates sequentially by instructing a base learner to merge its training set for predictions (Rincy and Gupta, 2020). Boosting trains weak classifiers sequentially, with each classifier trying to fix the previous one. It starts by estimating the dataset and each observation is given equal weight. The observations that were mistakenly anticipated in the preceding observation are given more weight in the subsequent iterations, and the errors of the preceding iterations are corrected. As an iterative process, adding classifiers continues until a limit is reached in the number of models or accuracy. Boosting method is calculated by equation 2 (Freund and Schapire, 1997; Akcan and Sertbaş, 2021).

$$H_{\mathrm{m}}(x) = \sum_{m=1}^{M} y_m \, h_m(x) \qquad [\mathrm{m}=1,\ldots,\mathrm{M}] \tag{2}$$

In Equation 2, y_m represents the target (m.) value; $\hbar\,(x)$ represents the base classifier and is chosen at each stage to minimize the loss function. The familiar Boosting algorithms are AdaboostM1, Total Boost, Gentle Boost, Logit Boost, and Robust Boost.

2.4.2. Bagging

Bagging (bootstrap aggreating) is a method of generating multiple versions of a base classifier by making bootstrapped copies of the training data and using them to generate a combined estimator (Agarwal and Chowdary, 2020). In the Bagging method, different training sets are created by taking random and repetitive samples from the entire data set. Each classifier is trained with a different training data. When classifying a new data, the result from each classifier is obtained and the final class label is determined by voting (Yıldırım et al., 2018). Bagging method is calculated by equation 3 (Breiman 1996; Akcan and Sertbaş, 2021).

$$c_{\mathrm{i}} = argmax_{\mathrm{i}} \, \{\frac{1}{N} \sum_{T=1}^{MN} h_T \,(x, c_i)\} \qquad [\mathrm{T}=1, \ldots, \mathrm{N}] \tag{3}$$

In Equation 3, $\hbar_T$ represents the prediction model and T represents the training subset. Average class score; takes the class predicted with the highest mean score calculated in all $\hbar_T$ (x, c_i) models.

2.5. Performance Evaluation Metrics

Sensitivity, Matthews correlation coefficient (MCC), accuracy, precision, f1 score, and specificity performance evaluation criteria were used to evaluate the success of the model.

These evaluation metrics are calculated using the false positive (FP), false negative (FN), true negative (TN), and true positive (TP) parameters in the confusion matrix. TP and TN parameters indicate the number of correctly labeled samples, while FP and FN parameters indicate the number of incorrectly labeled samples. Performance evaluation metrics formulas are given below.

$$\text{Accuracy} = (TN + TP) / (TN + FP + TP + FN) \tag{4}$$

$$\text{Sensitivity} = TP / (FN + TP) \tag{5}$$

$$\text{Precision} = TP / (FP + TP) \tag{6}$$

$$\text{F1- score} = 2 \text{ x Sensitivity x Precision} / (\text{Sensitivity} + \text{Precision}) \tag{7}$$

$$MCC = (TP \text{ x } TN - FN \text{ x } FP) / \sqrt{(FP + TP)x(TN + FN)x(FN + TP)x(TN + FP)} \tag{8}$$

$$\text{Specificity} = TN / (TN + FP) \tag{9}$$

The fact that, these performance evaluation metrics are close to 1 demonstrates that the proposed model did not achieve a random result and the performance of the model is quite high.

3. EXPERIMENTAL RESULTS AND DISCUSSION

The performances of ensemble learning methods for automatic detection of AD were compared using the PSD values of EEG signals calculated by the multitaper method. The EEG signals were recorded from 48 subjects, 24 healthy and 24 Alzheimer's patients. The PSD values of the frequencies between 1-49 Hz of the EEG signals were calculated using the multitaper method, 49 features were extracted. The PSD values obtained from the Fp1 channel by the multitaper method belonging to Alzheimer's and healthy groups are given in Figure 3. The PSD values obtained from other channels also have similar characteristics.

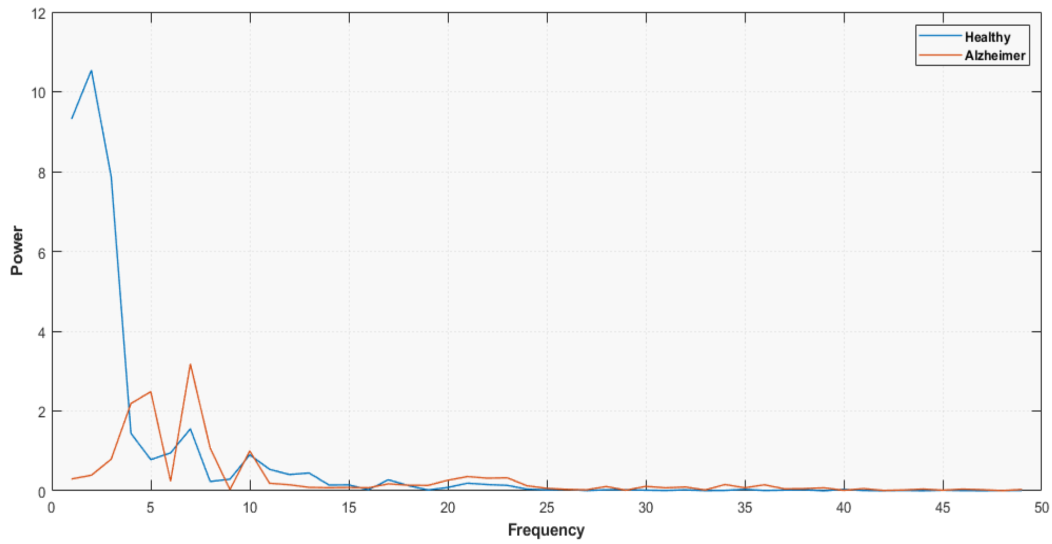

Figure 3:
PSD plot calculated by the multitaper

The EEG dataset used in the study contains a total of 912 EEG recordings (48 subject x 19 channels). The dataset was divided using the holdout method. 70% of the dataset was used for training (639), and 30% was used for testing (273). With this method, the data was divided into two non-overlapping parts and these two parts were used for training and testing, respectively. The model was designed with the training dataset and was tested with the testing dataset. The success of the model was tested with the testing dataset, which was not included in the design of the model. Confusion matrix parameters of ensemble learning methods (AdaboostM1, Total Boost, Gentle Boost, Logit Boost, Robust Boost, and Bagging), total correctly classified and total incorrectly classified data are given in Table 1.

Table 1. Confusion matrix of ensemble learning methods

Ensemble Learning Methods	Labels	Confusion matrix		Classified	
		HC	AD	Incorrectly (FP+FN)	Correctly (TP+TN)
AdaboostM1	HC AD	126 8	11 128	19	254
Total Boost	HC AD	120 11	17 125	28	245
Gentle Boost	HC AD	127 9	10 127	19	254
Logit Boost	HC AD	128 10	9 126	19	254
Robust Boost	HC AD	118 16	19 120	35	238
Bagging	HC AD	116 24	21 112	45	228

When Table 1 is examined, AdaBoostM1, Gentle Boost and Logit Boost algorithms are ensemble learning methods with the highest number of correctly classified data. The total number of correctly classified data was 254 (TP+TN) and the total number of incorrectly classified data was 19 (FP+FN) for these algorithms that showed the highest performance. The performance of the proposed model was evaluated with sensitivity, f1-score, specificity, MCC, precision, and accuracy model performance criteria calculated with TP, TN, FP, and FN parameters of ensemble algorithms. The performance results of the ensemble learning methods according to the model performance metrics are given in Table 2.

Table 2. Performance results of ensemble learning methods

Ensemble learning methods	Performance evaluation metrics (%)					
	Sensitivity	Specificity	Precision	MCC	F1- score	Accuracy
AdaboostM1	94.03	92.09	91.97	86.10	92.99	93.04
Total Boost	91.60	88.03	87.59	79.57	89.55	89.74
Gentle Boost	93.38	92.70	92.70	86.08	93.04	93.04
Logit Boost	92.75	93.33	93.43	86.08	93.09	93.04
Robust Boost	88.06	86.33	86.13	74.38	87.08	87.18
Bagging	82.86	84.21	84.67	67.05	83.75	83.52

F1-score and accuracy values should be especially examined in evaluating the success of the model. Accuracy is the ratio of correct predictions to the total dataset. The f1-score is the harmonic mean of the sensitivity and precision. While the distribution between the groups in the dataset is balanced, accuracy value produces more reliable results, while the f1-score can produce accurate results even when the distribution between unbalanced groups is uneven. For this reason, it is more appropriate to use the f1-score together with accuracy value in the evaluation of the developed models. In Table 2, the accuracy values of AdaboostM1, Gentle Boost and Logit Boost algorithms were 93.04%. The algorithm with the highest f1-score was the Logit Boost algorithm. As a result of the experiments, the highest performance according to both accuracy (93.04%) and f1-score (93.09%) values belonged to the Logit Boost algorithm.

The results of the Logit Boost ensemble learning algorithm, which demonstrated the highest performance in the study's proposed method, were compared with those of other studies that had been done in the past, including one that used EEG to diagnose Alzheimer's. Comparative analysis is given in Table 3.

Table 3. A comparative analysis with relevant literature studies

Researchers	Signal Processing	Dataset	Classifier	Accuracy
Fiscon et al. (2018)	Wavelet Transforms	72 (49 AD, 23 healthy)	Decision Trees	83.3%
Aslan (2022)	Wavelet Transforms	48 (24 AD, 24 healthy)	kNN	91.12%
Amini et al. (2021)	The time-dependent power spectrum	109 (49 AD, 37 MCI, 23 healthy)	CNN	89.1%
Ruiz-Gómez et al. (2018)	Spectral Analyses, Non-linear Analyses	111 (37 AD, 37 MCI, 37 healthy)	Multi-Layer Perceptron	78.43%
The proposed model	Multitaper	48 (24 AD, 24 healthy)	Logit Boost	93.04%

We presented an ensemble learning model to classify AD and HC groups with high accuracy. The results of this study discussed according to feature extraction method, classification algorithms, and accuracy. The multitaper method prevents data loss and reduces prediction bias, as modified periodograms calculated using a series of mutually orthogonal windows or tapping were averaged to generate a consistent estimate of PSD (Candy, 2019). Therefore, the multitaper method was adopted for feature extraction in the study. When the methods used in studies in the related literature are examined, wavelet transforms (Fiscon et.al, 2018; Aslan, 2022), spectral and non-linear analysis (Ruiz-Gómez et.al. 2018), and the time-dependent power spectrum methods (Amini et.al, 2021) were used for feature selection of EEG signals. The ensemble learning algorithm adopted in this study, because ensemble learning combines the strengths of multiple classification algorithms. When EEG-based AD studies are examined in Table 3, algorithms used in the recent literature were decision trees (Fiscon et.al, 2018), kNN (Aslan, 2022), CNN (Amini et.al, 2021), and Multi-Layer Perceptron (Ruiz-Gómez et.al. 2018). Experiment results showed that the highest accuracy (93.04%) was achieved with the Logit Boost method of the ensemble learning algorithm in this study. The accuracy of the proposed model was more successful than the models in the relevant literature in Table 3 (Fiscon et.al, 2018; Aslan, 2022; Ruiz-Gómez et.al., 2018; Amini et.al, 2021). The main reasons for this success were the use of ensemble learning and multitaper methods in the study. Because ensemble learning algorithm was effective in reducing high variance compared to many individual classification algorithms such as Naive Bayes, SVM, or kNN, and also provides increased performance by reducing bias. It also removed the weaknesses of these individual classification algorithms in a given condition in the classification task. Moreover, using the multitaper method for feature extraction prevented data loss and improved classification success by reducing prediction bias.

4. CONCLUSION

Consequently, we proposed a model that effectively combines multitaper and ensemble learning methods using EEG signals for early diagnosis of AD. In the experiments, firstly, feature extraction was performed by using the PSD values of the frequencies between 1-49 Hz of the EEG signals with the multitaper method, and 49 features were extracted. Then, the performances of AdaboostM1, Total Boost, Gentle Boost, Logit Boost, Robust Boost, and Bagging ensemble learning methods were compared. Experimental results show that the algorithm with the highest performance was achieved with the Logit Boost ensemble learning algorithm. The algorithm had a promising performance of 93.04% accuracy, 93.09% f1-score, 92.75% sensitivity, 93.43% precision, and 93.33% specificity. The fact that, the values of these performance evaluation criteria are quite high demonstrates that the model does not have a random success. The proposed model can support expert for diagnosis of AD and can be applied to different biomedical signals.

CONFLICT OF INTEREST

The author confirms that there is no known conflict of interest or common interest with any institution/organization or person.

AUTHOR CONTRIBUTION

Hanife Göker: Designing concepts of the study, data analysis and data interpretation, implementation of methods and writing the draft of the manuscript

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