Research Article

Diagnosis of Alzheimer's Disease using EEG Signals

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Abstract

Alzheimer is a common and significant neurological disorder worldwide, typically associated with age-related dementia. Alzheimer's patients exhibit slower brain activities compared to healthy individuals, and the most prominent symptom of the disease is the impairment of cognitive functions. Early diagnosis of Alzheimer's is crucial to prevent the rapid progression of the disease. In this study, the feasibility of using electroencephalography (EEG) signals, a non-invasive, cost-effective, and objective method, to facilitate the diagnosis of Alzheimer's Disease (AD) was investigated.
The study utilized EEG signals from both Alzheimer's patients and healthy individuals, which were made publicly available by Florida State University. Preprocessing was applied to the EEG signals to eliminate existing noise. Subsequently, a total of 34 various features in the time and frequency domains, such as entropy, Hjorth parameters, etc., were extracted from the EEG signals for the purpose of Alzheimer's diagnosis. Machine learning techniques, including decision trees (DT), support vector machines (SVM), and artificial neural networks (ANN), were applied to classify the data, and success rates for Alzheimer's detection were achieved.

Keywords: *Alzheimer's Disease, EWT, EEG, Classification.*

1. Introduction

Alzheimer's disease takes its name from the German psychiatrist and pathologist Alois Alzheimer, who first described it in 1906. As of 2020, Alzheimer's disease has been observed in approximately 50 million people worldwide, with cases primarily occurring in individuals aged 65 and older. The onset of Alzheimer's is seen in about 10% of people in their 30s to 60s. Among individuals aged 65 and older, approximately 6% have

Alzheimer's disease. Alzheimer's disease is more commonly observed in women than in men [1].

Alzheimer's disease develops due to the abnormal accumulation of a protein called beta-amyloid in the brain's nerve cells. Over time, these proteins increase and cannot be cleared from the brain tissue. As a result of protein buildup, the connections between nerve cells break, and nerve cells begin to die. This leads to the brain's inability to perform its normal functions. The rapid cell death in the brain causes it to shrink and reduce in volume.

The disease initially leads to mild forgetfulness that may not be considered significant, but these symptoms gradually increase and affect the person's memory, starting from today and extending backward into the past [2].

While there is no cure for Alzheimer's disease, in its advanced stages, complications arising from severe cognitive decline, such as dehydration, inadequate nutrition, or infections, can lead to the person's death [3]

Since there is no definitive cure for Alzheimer's disease, early diagnosis of the disease is crucial to reduce its devastating effects, address some of its symptoms, allow patients and their families to plan for the disease's progression, and minimize the personal and societal costs associated with it. Various biomedical imaging techniques, such as CT (Computed Tomography), MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography), and fMRI (Functional Magnetic Resonance Imaging), are used in the diagnosis of Alzheimer's disease. In addition to these methods, EEG signals can also be utilized for disease diagnosis due to their lower cost and time requirements compared to other techniques.

There are various studies in the literature concerning the diagnosis of Alzheimer's disease using EEG signals. Safi and colleagues [4] evaluated EEG signals obtained from 35 healthy individuals, 31 mild Alzheimer's patients, and 20 moderate Alzheimer's patients using different methods, including Hjorth parameters, signal filtering, discrete wavelet transform (DWT), empirical mode decomposition (EMD), support vector machine (SVM), K-nearest neighbors (KNN), and regularized linear discriminant analysis (RLDA). As a result of the study, they achieved an accuracy rate of 97.64% using Hjorth parameters, DWT method, and KNN classification algorithm. Afsa and colleagues [5] applied median filtering to EEG signals obtained from a total of 12 individuals to remove noise, then separated the signal into sub-bands using dual-tree complex wavelet transform and compared healthy individuals, Alzheimer's patients, and individuals with the onset of Alzheimer's using artificial neural networks (ANN). They obtained an accuracy rate of 95% in distinguishing between healthy individuals, Alzheimer's patients, and those with the onset of Alzheimer's by comparing the 6 features consisting of mean, variance, standard deviation, and others with the same features obtained from a total of 30 healthy and patient data available in the database. Deshmukh and colleagues [6] initially applied a Butterworth filter (0-60 Hz) to remove noise from EEG signals, divided the signal into 60-second windows, and then applied DWT to obtain features such as mean, standard deviation, kurtosis, skewness. They achieved an accuracy rate of 97.61% by classifying with SVM, KNN, and ANN.

The aim of this article is to perform a high-accuracy classification study for the diagnosis of Alzheimer's disease using machine learning algorithms with feature vectors obtained by extracting various spectral and statistical features from EEG signals.

2. Materials and Methods

In this section, information about the materials and methods used in the study is provided. Initially, a 30 Hz cutoff frequency FIR filter was applied to the EEG signals to eliminate environmental noise, and band decomposition was carried out using empirical wavelet transform (EWT). Feature vectors in the time and frequency domains for each patient were obtained from EEG signals with and without band decomposition. The obtained data underwent chi-square feature selection, and classification was performed using SVM, ANN, and DT algorithms with leave-one-out cross-validation (LOOCV) and 10-fold cross-validation applied separately for 5, 10, 50, and 100 features. The workflow of the study is presented in the diagram below.

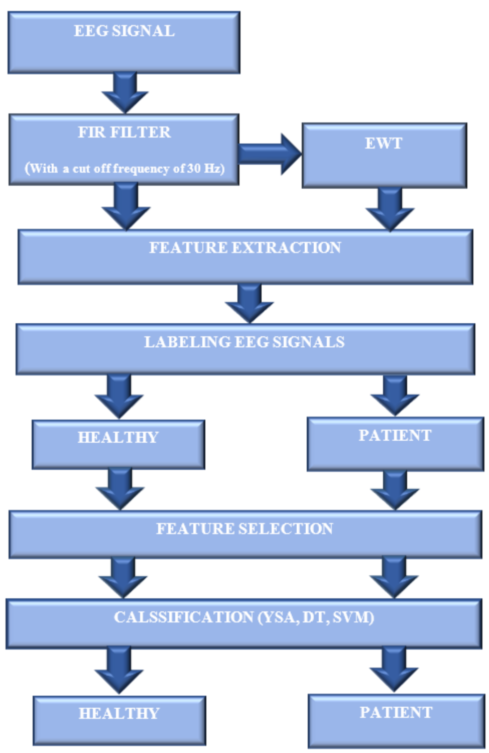

Figure 1: Process Flowchart

2.1. EEG Dataset

In this study, an EEG dataset made publicly available by Florida State University was utilized. The recordings were obtained from 24 healthy individuals with an average age of 72 and 24 individuals with an average age of around 69 diagnosed with Alzheimer's disease (AD). A recording system with 19 electrodes, adhering to the international 10-20 system, and utilizing the Biologic Systems Brain Atlas III Plus workstation was used. The recordings were divided into four groups, consisting of groups A and B for healthy individuals and groups C and D for patients. The recordings were acquired with a sampling frequency of 128 Hz for a duration of 8 seconds. Groups A and C had their eyes open with a fixed visual focus, while groups B and D had their eyes closed [7].

2.2. Feature Extraction

The feature extraction stage for EEG signals and other biomedical signals is highly important for reducing the dimensionality of a dataset by removing unnecessary data while preserving valuable information, thereby leading to various benefits such as reducing computation, enhancing learning and training speed, and improving model accuracy.

In this study, a total of 34 spectral and statistical features, such as Hjorth parameters, entropy, maximum, standard deviation, mean, minimum, band powers, etc., for each channel were extracted from EEG signals using the Matlab EEG Feature Extraction Toolbox.

2.3. Feature Selection

Feature selection, defined as the selection of the best subset that can represent the original dataset, aims to reduce the number of features in a dataset by choosing the most beneficial and crucial features for the problem at hand. It seeks to decrease data dimensionality, improve data quality, eliminate irrelevant and noisy data, and enhance the success of the obtained model [8].

Various methods are employed for feature selection. In this study, the chi-squared method was utilized. The Chi-Merge algorithm, initially developed by Kerber in 1992, was later refined by Liu and Setiono in 1995. The chi-squared value is calculated to measure the dependency of a factor within the dataset on the class [9]

2.4. Classification Algorithms

Classification algorithms are a technique used to categorize new data based on training data. In classification, a program first learns the data, or in other words, is trained, and then it assigns new data to one or more classes or groups based on this training [10].
In this study, classification was performed using decision trees (DT), support vector machines (SVM), and artificial neural networks (ANN) with the MATLAB software, which is a programming and numerical computing application developed by MathWorks and used for data analysis, algorithm development, and model creation. The performance of these models was evaluated using a confusion matrix and ROC curve.

2.4.1. Desicion Trees

Decision tree algorithms rank features based on their importance in separating the data. The most effective feature in data separation is placed at the root node of the tree, and the data is classified accordingly. Subsequently, the most effective feature in distinguishing the data is reevaluated in a sequential manner. Therefore, through this iterative process, a classification tree is created [11].

2.4.2. Artificial Neural Networks

Artificial Neural Network (ANN) is a machine learning technique designed by taking inspiration from the human nervous system and thinking ability, which can provide solutions to problems that remain unsolved in traditional machine learning techniques due to its complex learning capability. Thanks to its learning capability, ANN can generate information about events that have not occurred using past data or known examples and make generalizations. ANN primarily works with numerical data and is commonly used in data clustering, prediction, and classification processes [12].

2.4.3. Support Vector Machines

Support Vector Machines (SVM) is one of the most commonly used classification algorithms. In addition to linear classification, SVM can efficiently perform nonlinear classification by indirectly mapping input data into a high-dimensional feature space. The fundamental concept behind SVM is based on drawing margins between classes, and these margins are drawn to maximize the distance between the margin and the classes to minimize classification errors [13].

2.5. Performance Metrics

Evaluating a machine learning model or deep learning model's effectiveness is crucial. In this study, confusion matrix, accuracy, precision, recall, specificity, negative predictive value, F1 score, and AUC values were used to assess the applied classification algorithms.

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2.5.1. Confusion Matrix

The confusion matrix is a tabular representation of a classification model's performance, where each data point in this matrix shows the count of predictions made by the algorithm, whether correct or incorrect. Classification models trained with labeled data are split into testing data, and after training, they validate against known labeled data, generating a prediction label that represents the model's prediction outcome [14].

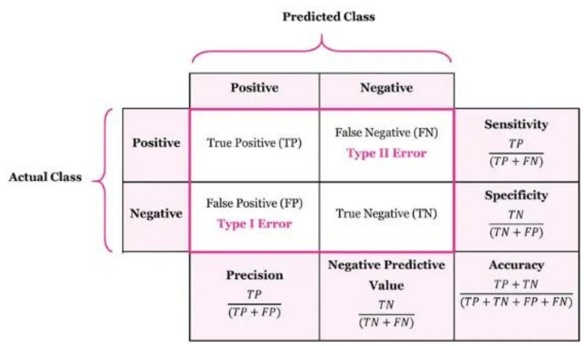

Figure 2: Confusion Matrix [14]

2.5.2. AUC-ROC Curve

One of the most important evaluation metrics used in performance measurement of classification problems is the AUC-ROC curve. It is particularly one of the most commonly used parameters for performance assessment of machine learning algorithms, especially in datasets with irregular distributions. The ROC curve generally indicates how well the model performs in making predictions [15].

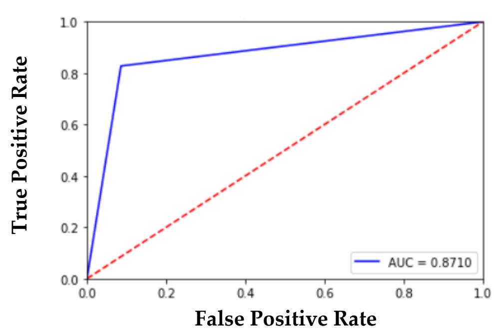

Figure 3: ROC Curve

3. Results

In this study, EEG signals were denoised using a FIR filter, followed by feature extraction for each channel, including kurtosis, skewness, median, etc., with and without band decomposition. Feature selection was performed using the chi-square method, and 10-fold cross-validation and leave-one-out cross-validation (LOOCV) validation methods were applied for 5, 10, 50, and 100 features. Classification was carried out using SVM, ANN, and DT algorithms, and various performance metrics were obtained for these classification algorithms. Band decomposition was applied to EEG signals using the EWT method, which is commonly used for the analysis of non-stationary or non-repeating signals.

When band decomposition was performed with the EWT method in the eyes-open condition, the DT classification algorithm achieved the best performance values for 10-fold cross-validation and LOOCV validation with 100 features, with accuracy, specificity, sensitivity, and F1 score metrics all being 1. The ANN classification algorithm achieved the best performance values, which were 0.99, 0.99, 1, and 0.99, respectively. The SVM classification algorithm's best performance values were 0.99, 0.99, 1, and 0.99. When all these data were evaluated for the eyes-closed condition, the DT classification algorithm's best performance values were 0.95, 0.91, 1, and 0.99, respectively, while the ANN classification algorithm's best performance values were 0.99, 0.99, 1, and 0.99, and the SVM classification algorithm's best performance values were 1 for all metrics. An overall assessment for all the data showed that the DT classification algorithm's best performance values were 0.95 for all metrics, the ANN classification algorithm's best performance values were 1 for all metrics, and the SVM classification algorithm's best performance values were 0.99, 0.99, 1, and 0.99.

When band decomposition was not performed with the EWT method in the eyes-open condition, the DT classification algorithm achieved the best performance values for 10-fold cross-validation and LOOCV validation with 100 features, with accuracy, specificity, sensitivity, and F1 score metrics all being 1. The ANN classification algorithm's best performance values were 1 for all metrics, while the SVM's best performance values were 0.89, 0.91, 0.87, and 0.89, respectively. When all these data were evaluated for the eyes-closed condition, the DT classification algorithm's best performance values were 0.91 for all metrics, the ANN classification algorithm's best performance values were 0.97, 0.96, 0.99, and 0.98, and the SVM classification algorithm's best performance values were 0.94, 0.91, 0.96, and 0.94, respectively. An overall assessment for all the data showed that the DT classification algorithm's best performance values were 0.88, 0.84, 0.92, and 0.88, the ANN classification algorithm's best performance values were 0.99, 1, 0.98, and 0.99, and the SVM classification algorithm's best performance values were 0.94, 0.95, 0.93, and 0.94.

Table 1: Performance Metrics Obtained From Classification Conducted With SVM, ANN, and DT Algorithms

	Year	Preprocessing	Feature Extraction	Classification	AD	Control	Accuracy	Specificity	Precision	F1 Skor
1. Method (All data-For 100 features)	2023	FIR Filter	Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	SVM	24	24	94%	95%	93%	94%
		FIR Filter	Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	YSA	24	24	99%	100%	98%	99%
		FIR Filter	Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	DT	24	24	88%	84%	92%	88%
2. Method (All data-For 100 features)	2023	FIR Filter	EWT, Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	SVM	24	24	99%	99%	100%	99%
		FIR Filter	EWT, Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	YSA	24	24	100%	100%	100%	100%
		FIR Filter	EWT, Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	DT	24	24	95%	95%	95%	95%
3. Method (Eyes open- For 100 features)	2023	FIR Filter	Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	SVM	12	12	89%	91%	87%	89%
		FIR Filter	Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	YSA	12	12	100%	100%	100%	100%
		FIR Filter	Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	DT	12	12	100%	100%	100%	100%
4. Method (Eyes open- For 100 features)	2023	FIR Filter	EWT, Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	SVM	12	12	99%	99%	100%	99%
		FIR Filter	EWT, Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	YSA	12	12	99%	99%	100%	99%
		FIR Filter	EWT, Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	DT	12	12	100%	100%	100%	100%

		FIR Filter	Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	SVM	12	12	94%	91%	96%	94%
5. Method (Eyes closed- For 100 features)	2023	FIR Filter	Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	YSA	12	12	97%	96%	99%	98%
		FIR Filter	Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	DT	12	12	91%	91%	91%	91%
		FIR Filter	EWT, Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	SVM	12	12	100%	100%	100%	100%
6. Method (Eyes closed- For 100 features)	2023	FIR Filter	EWT, Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	YSA	12	12	99%	99%	100%	99%
		FIR Filter	EWT, Band Power Ratios, Skewness, Kurtosis, Hjorth Parameters, etc. totaling 34 Features, Chi-Square	DT	12	12	95%	91%	100%	96%

In summary, without band decomposition, ANN demonstrated the best performance for eyes-open, eyes-closed conditions, and all data. However, when band decomposition was performed using the EWT method, ANN achieved the best performance for all data, DT for the eyes-open condition, and SVM for the eyes-closed condition, all achieving 100% success. When an overall assessment of the study was conducted, it was observed that the performance metrics obtained with the EWT method for EEG signals yielded better results when compared to the performance metrics obtained without band decomposition.

In Table 2 below, performance results from various studies in the literature are presented. Since the number of patients and healthy individuals used in these studies, as well as factors such as noise, may vary, it is considered that a direct one-to-one comparison of the values in the table cannot be made with our thesis study. However, when making a comparison independent of all these factors, it is observed that the performance metrics obtained with the methods applied in this study achieve a higher success compared to the values given in the table.

Tablo 2: Literature Reviews

Authors	Year	Preprocessing	Feature Extraction	Classification	AD	Control	Accuracy	Specificity	Precision	Other
Deshmukh et all. [6]	2022	Butterworth Bandpass Filter, Notch Filter	DWT, Mean, Variance, Standard Deviation, Skewness, Kurtosis	SVM, KNN, Convolutional Neural Networks (CNN)			97,61%			
Bairagi, V. [16]	2018	Butterworth Bandpass Filter	DWT, Power Spectral Density (PSD)	KNN, SVM	24	24	94%			
Kulkarni et all. [17]	2014	Blind Source Separation (BSS), Independent Component Analysis (ICA)	Wavelet Transform (WT), Fast Fourier Transform (FFT), Thinning and Cross Modeling, Autoregressive Model (AR)	Linear Discriminant Analysis (LDA), SVM			95%			
Alsharabi et all. [18]	2022	Bandpass Digital Elliptic Filter	DWT, Logarithmic Band Power, Standard Deviation, Variance, Kurtosis, Mean Energy, Root Mean Square, Norm	Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM), Naive Bayes (NB), K-Nearest Neighbors (KNN), Decision Tree (DT), Extreme Learning Machine (ELM), Artificial Neural Network (ANN), Random Forest (RF)	51	35	99,98%	99,98%		
Biagetti et all. [19]	2021		Principal Component Analysis (PCA), Robust Principal Component Analysis (R-PCA)	KNN, DT, SVM and NB	7	6	93.18%			
Safi et all. [4]	2021	Chebyshev Type II Bandpass Filter	DWT, EMD, FFT, Hjorth Parameters, Variance, Kurtosis, Skewness, Shannon Entropy, Approximate Entropy	Multi-Class Support Vector Machines (MSVM), K-Nearest Neighbors (KNN), Regularized Linear Discriminant Analysis (RLDA)	51	35	97,64%	98,81%	95,40%	
Kim et all. [20]	2005			Combined Genetic Algorithms (GA), Artificial Neural Network (ANN)	16	10	-	-	-	Absolute recognition rate 73%
Lehmann et all. [21]	2007		FFT, Global Time Domain, Absolute and Relative Spectral Power	Principal Component Linear Discriminant Analysis (PC LDA), Partial Least Squares LDA (PLS LDA), Principal Component Logistic Regression (PC LR), Partial Least Squares Logistic Regression (PLS LR), Bagging, Random Forest, SVM, Feedforward Neural Network (NNET)	197	45	-	88%	89%	-

Akrofi et all. [22]	2008		Multiple Discriminant Analysis, k-Means Clustering	Coherence-Based Automatic AF Detection System	16	16	-		-	Total classification rate 83,99%
Ahmadlou et all. [23]	2010		WT, Complexity Graph Dependent on the Maximum Eigenvalue of the Adjacency Matrix, Scale-Free Strength of the Graph Structure	Radial Basis Function Neural Network (RBFNN) Principal Component Analysis (PCA) - Radial Basis Function Neural Network (RBFNN)	20	7	97,75%	91,08%	100%	-
Falk et all. [24]	2012	Infinite Impulse Response Low-Pass Elliptic Filter	Percentage Modulation Energy, AUC-Based Feature Selection Algorithm	SVM	21	11	90,60%	90,90%	90,50%	-
Ghorbanian et all. [25]	2012		DWT, T-Test, Kruskal-Wallis Test, Absolute Mean Power, Standard Deviation	DT	10	14	-	-	-	Confidence 100%

4. Discussion and Conclusion

The aim of this study is to facilitate the diagnosis of Alzheimer's disease (AD), which is challenging, costly, and time-consuming, by using EEG signals that are both cost-effective and non-invasive. The study also aims to contribute to the disease's treatment process. EEG signals from individuals with AD and healthy subjects exhibit differences. AD is characterized by slowing down of EEG signals, reduced complexity, and synchronization loss. Therefore, in this study, various spectral and statistical features were extracted from EEG signals. These features were subjected to chi-squared feature selection, 10-fold cross-validation, and leave-one-out cross-validation (LOOCV), and classification was performed using machine learning algorithms, including SVM, ANN, and DT. When we look at the highest performance values obtained in the results from our study for 5, 10, 50, 100 features, open-eye, closed-eye conditions, and all data, we achieved a 100% accuracy rate separately with the DT, SVM, and ANN classification algorithms.

With the conducted study, using EEG signals, individuals with Alzheimer's disease (AD) and healthy subjects could be distinguished with higher accuracy compared to other studies in the literature. Furthermore, the proposed system can be used as a computer-aided diagnostic system to assist healthcare professionals in diagnosing AD.

5. Acknowledge

In the prepared article, there is no need for ethics committee approval. There are no conflicts of interest with any individual or institution in the prepared article.

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