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A NEW COMPUTATIONAL APPROACH FRAMEWORK FOR THE DIAGNOSIS OF ALZHEIMER'S DISEASE

Zulfikar ASLAN

Vocational School of Technical Sciences
Gaziantep University, Gaziantep 27310, Türkiye
zulfikaraslan27@gmail.com

ABSTRACT

Alzheimer's disease (AD) represents a significant neurological disorder with a wide prevalence worldwide, characterized by cognitive and behavioral deficits resulting from brain degeneration. Despite extensive research efforts, a cure for AD has yet to be found. However, detecting the disease at its early stages can aid in slowing down its progression. However, accurate diagnosis of AD involves costly and arduous testing procedures that necessitate the evaluation of an experienced specialist. To address this, a new computer-aided diagnosis (CAD) system with high performance has been proposed to automatically diagnose AD using EEG signals. The MSPCA method was used for preprocessing to eliminate existing noise, followed by the application of the TQWT signal decomposition technique to EEG data. The Hjorth parameters, derived from the recorded data, were obtained as distinctive attributes for subsequent analysis, and the resulting features were tested using various classification algorithms. The obtained features were evaluated using different statistical techniques to determine their classification performance in distinguishing AD patients from healthy individuals. The results revealed that the k-nearest neighbor (KNN) classifier yielded the highest classification performance of 99.78%±0.004. The methodological framework under investigation, which draws on the Tunable Q-factor Wavelet Transform (TQWT), was evaluated through the application of diverse signal separation methodologies. The results indicate that the proposed approach outperformed other techniques in AD diagnosis. As such, the present study puts forth a Computer-Aided Diagnosis (CAD) framework that holds promise in augmenting the proficiency of experts in the diagnosis of Alzheimer's disease.

Key Words: TQWT, EEG, Alzheimer Diagnosis, Hjorth Parameter

1. INTRODUCTION

AD is a major neurological disorderliness that is prevalent on a global scale and is the most frequent form of dementia associated with aging. AD patients exhibit slower brain activities compared to healthy individuals, and the most prominent symptom is the progressive deterioration of cognitive functions. In 2018, approximately 50 million people were affected by this disease globally. Based on projections, the numerical quantity in question is anticipated to experience an upsurge, with estimates suggesting an expansion to 82 million by the year 2030 and continued growth in the future. AD is classified into three categories: mild, moderate, and severe. At all stages of the disease, individuals with AD experience a gradual decline in cognitive functions. Early detection of AD is crucial to impede the rapid progression of the disease. Consequently, several studies have been conducted on the diagnosis of AD [1]–[3].

Electroencephalography (EEG) signals represent a critical instrument that is extensively employed to examine brain function. As EEG signals necessitate reduced costs and time in comparison to other biomedical imaging methods, such as magnetic resonance imaging (MRI), positron emission tomography (PET), computed tomography (CT), and functional magnetic resonance imaging (fMRI), The usage of these methods is common in the advance of computer-aided diagnosis (CAD) systems that are utilized for the diagnosis of different ailments. Apart from the aforementioned biomedical imaging modalities, several research studies have explored the classification of EEG signals using machine learning algorithms to differentiate AD in the existing literature [4]–[9].

Kulkarni et al. [4] conducted a study on diagnosing AD using various feature extraction techniques such as Spectral features, wavelet features, and complexity features from EEG signals. The Support Vector Machine (SVM) algorithm was employed to perform feature classification on the data, resulting in a classification accuracy of 86% for Spectral features, 88% for wavelet features, and 96% for complexity features. In a similar study, Bairagi [1] obtained spectral and wavelet-based features and classified them with KNN and SVM algorithms, achieving the highest classification accuracy of 94% by classifying spectral-based features with the SVM algorithm. Ruiz-Gómez et al. [5] combined the spectral and nonlinear features from EEG signals and classified them using different machine learning algorithms. The highest accuracy rate of 78.43% was achieved with Quadratic Discriminant Analysis (QDA) and Multi-Layer Perceptron (MLP) algorithms. Amezquita-Sanchez et al. [6] applied the process of categorizing multiple signals based on certain criteria and empirical wavelet transform to EEG signals to diagnose AD and achieved 90.3% accuracy by classifying features with the advanced probabilistic (EPNN) classifier. In Kulkarni's study [7], the spectral and complexity features obtained from EEG signals were combined and classified using the KNN classifier, resulting in the highest accuracy of 94%. Tzimourta et al. [8] tested statistical and spectral properties calculated from EEG signals with different classification algorithms and obtained 88.79% accuracy by classifying features with the Random Forest classifier. According to Safi et al. [9], a classification performance of 97.64% was achieved by classifying wavelet-based features calculated from EEG signals. The proposed method was successful in distinguishing AD and healthy subjects. In their study, Safi et al. conducted experiments to evaluate the effectiveness of Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD) methods for the detection of AD. They used Hjorth parameters as features to classify the EEG signals. They achieved the best classification accuracy of 97.64% using the KNN classifier with the features extracted by the DWT method.

Although various algorithms and processing techniques were used in these studies, some limitations affecting the performance of CAD systems for diagnosing AD from EEG signals include the inability to determine appropriate feature selection methods and the failure to consider the EEG channels carrying the necessary information.

In recent times, the use of TQWT in the examination of brain signals has been increasingly adopted [10]–[20].

Hassan et al. demonstrated highly effective classification accuracy in the detection of epileptic seizures using a method that involves EEG recordings and the TQWT technique [16]. Murugappan et al. conducted a research study aiming to investigate the correlation between Parkinson's disease and emotional dysregulation by analyzing EEG data. The investigation under consideration examined six distinct mood states. TQWT was used in their proposed method for the purpose of analyzing EEG signals, and the statistical properties were classified using the KNN classification algorithm, resulting in promising outcomes [12]. Taran et al. conducted a study utilizing the TQWT methodology, aiming to categorize motor vision tasks by analyzing EEG recordings [17]. Patidar et al. conducted a separate inquiry involving the introduction of a TQWT approach-based technique that utilizes EEG data for the purpose of epilepsy detection [14]. Furthermore, Patidar et al. proposed a CAD approach that draws on the TQWT and utilizes EEG data for the purpose of coronary artery disease detection. [15]. Bajaj et al. put forward a methodology that utilizes the TQWT approach to categorize wakefulness and drowsiness states through EEG recordings. The authors demonstrated highly satisfactory performance of their proposed method for the classification of these states [18]. Zeng et al. conducted a study on the automatic detection of cardiac arrhythmia using various separation techniques in ECG recordings. The researchers utilized the TQWT technique in their proposed methodology, achieving the greatest degree of precision, as reported at 98.72%. They subsequently conducted comparative analyses of their outcomes with alternative separation methods [11]. Patidar et al. employed the TQWT technique in order to discriminate between EEG data of alcoholic individuals and those of normal controls. The study also explored the influence of the Q value on classification in their method [13]. Liu et al. utilized TQWT for the identification of myocardial infarction in ECG recordings. They evaluated the efficacy of their proposed method against other decomposition approaches and determined that the Tree Bagger classifier demonstrated the most outstanding performance, achieving an accuracy of 99.98% [10]. In a study presented by Aslan, a TQWT-based approach was presented in the diagnosis of migraine disease, and results with very high performance were obtained with the proposed method [20].

The principal explanation for the TQWT's superior classification efficiency is its capacity to provide a very adaptable and wholly distinct wavelet transform that is especially suitable for the study of oscillatory signals [13]–[16]. Conventional wavelet transforms are unable to adjust Q factors, while TQWT is capable of adjusting Q factors, which makes it a potent tool for analyzing oscillating signals. Several methods have been used in literature for the purpose of extracting informative features from signals such as filtering, power spectrum analysis, FFT, and wavelet transform. However, these methods have certain limitations. To illustrate, techniques for filtering and analyzing the power spectrum necessitate the meticulous process of selecting the limits for a filter, while Fast Fourier Transform (FFT) techniques suffer from a localization issue. On the other hand, wavelet transforms necessitate an appropriate selection of decomposition levels and primary wavelets, which can present challenges. Due to the aforementioned limitations of other methods, TQWT has been utilized for independent component analysis of EEG signals as it does not require the selection of a specific wavelet function [12], [17], [18].

In recent years, there has been a surge in the number of research studies that employ Hjorth parameters as a tool for extracting meaningful information from various biomedical signals. The Hjorth parameters have been utilized in several literature studies focused on computer-aided diagnosis (CAD), such as heart rate detection from electrocardiogram (ECG) signals [21], the classification and definition of lung sounds [22], [23], the classification of electromyogram (EMG) signals [18], and the diagnosis of conditions such as hyperactivity (ADHD) and epilepsy [24]–[26].

The main motivation was that both TQWT and Hjorth parameters offer high classification success despite low computational complexity. In the known literature studies based on the CAD system that diagnoses AD from the EEG signal, no study using TQWT and Hjorth parameters together has been found. The initial phase of the study involved splitting EEG data into different subbands through the use of TQWT after employing the MSPCA technique to eliminate noise. Subsequently, feature extraction was performed on every subband, and to evaluate the approach, several learning algorithms (e.g., KNN, SVM, and MLP) were employed, which are often used as benchmarks for feature classification. The proposed technique demonstrates a remarkable classification accuracy of 99.78%±0.004% when implemented with the KNN classifier, and it also exhibits a low computational complexity, rendering it highly efficient. Furthermore, the proposed method shows superior performance in comparison to the currently available literature.

The significant advancements and novel contributions of this paper's methodology can be listed as follows, taking into account its impact on the field of study and its practical applications in real-world scenarios:

1. The proposed methodology employs a novel approach that combines Hjorth parameters and the TQWT method to create an automated diagnostic system for detecting AD using EEG signals.
2. The performance evaluation of Hjorth parameters for distinguishing between individuals with AD and healthy individuals was conducted using commonly employed statistical tests in literature, such as the t-Test, Wilcoxon rank-sum, and Kolmogorov-Smirnov test.
3. Assessing the performance of the methodology in discrimination AD based on electrode signals.
4. The study involved evaluating the classification performance of the extracted features using various conventional classification algorithms such as SVM,

KNN, and MLP, which are widely recognized as benchmarks in related literature.
5. The study involved comparing the proposed method's computational complexity and classification performance to those of other decomposition methods through a comprehensive analysis.
6. To enhance the classification performance of AD diagnosis based on EEG signals while considering the existing literature on CAD studies.

2. METHODOLOGY

This section contains data set definitions and proposed methodology design, respectively. The flowchart of the presented study aimed at automatic AD diagnosis with high performance is shown in Figure 1.

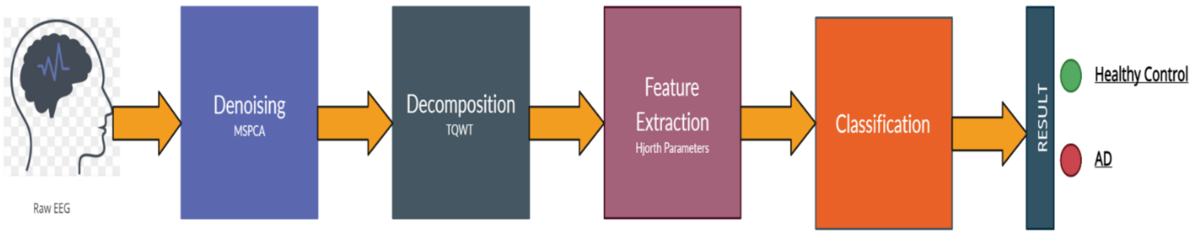

Figure 1. Flowchart showing the stages of the presented work

The methodology expounded in the investigation comprises the subsequent phases:

1. The elimination of extraneous noise from the signal was accomplished through the application of the MSPCA method;

2. The signal was decomposed into subbands using the TQWT approach;

3. Calculation of Hjorth parameters;

4. Evaluating the discriminatory ability of the features extracted from the signal to differentiate the disease using statistical tests;

5. On the basis of electrodes, the proposed method was classified and compared with various classifiers;

6. In addition, testing the signal separation methods commonly used in the literature and testing the results with the presented method.

Dataset Descriptions and Preprocessing Phase

In a study conducted by Florida State University researchers, the data set recorded in the Biological Systems Brain Atlas III Plus workstation using a 19-electrode recorder that electrode placement followed the guidelines of the international 10-20 system was used in this study. Recordings of the four groups (A, B, C, D) were made under two different resting conditions. Groups A and C, which underwent visual fixation, were recorded with open eyes, while groups B and D were recorded with closed eyes. Groups A and B consisted of 24 healthy elderly individuals aged 61-83 years, while groups C and D consisted of individuals aged 53-85 years diagnosed by the National Institute of Neurological and Communication Disorders and Stroke (NINCDS) and Alzheimer's Disease and Related Disorders Association (ADRDA).

It consists of 24 possible AD patients. In the conducted study, EEG recordings were obtained for a fixed time interval of 8 seconds and the frequency range of the signals was limited to the band of 1-30Hz. The sampling frequency for the recordings was set at 128Hz, and a technician was assigned to monitor the patient's alertness throughout the recording process. Furthermore, the dataset utilized in this study is available as open source, with the corresponding source code being denoted as [27].

MSPCA is an innovative technique that merges the advantages of both Principal Component Analysis (PCA) and wavelet analysis. Wavelet technique is implemented to calculate deterministic characteristics, whereas PCA methodology is utilized to discern a linear correlation between the said features.

This combination of techniques makes MSPCA a powerful tool for the analysis and noise removal of varying signals, especially due to its multi-scale capability. MSPCA is capable of effectively filtering out residues and scores with high efficiency. Given these considerations, the study utilized MSPCA to proficiently eliminate noise from the signal [28].

Decomposition of EEG Data

TQWT is a methodology for analyzing a system or phenomenon at multiple scales, commonly known as a multi-scale analysis technique that permits the analysis of signals in both the time and frequency domains. It is based on the principles of wavelet theory and provides a way to analyze signals at different scales and resolutions. The TQWT method uses a series of filters that operate on the input signal, each with a different center frequency and Q-factor. The Q-factor determines the width of the frequency band that each filter will pass, with higher Q-factors resulting in narrower bands. By adjusting the Q-factor of each filter, the TQWT method can provide a tunable frequency resolution, allowing for a more precise analysis of the signal. The TQWT method is typically applied in a recursive manner, with each level of the transform dividing the input signal into frequency sub-bands and applying the same set of filters to each sub-band. This procedure generates a hierarchical representation of the input signal that encompasses multiple scales, where the lowest scale characterizes the low-frequency components and the highest scale characterizes the high-frequency components. The TQWT method has several advantages over other wavelet transforms. For example, the tunable Q-factor allows for a more precise analysis of the signal, and the multi-scale representation provides a comprehensive view of the signal at different scales. Additionally, the TQWT method is computationally efficient and can be easily implemented on a digital signal processor. In conclusion, The TQWT approach is a robust and effective technique for conducting time-frequency analysis of signals. Its tunable Q-factor and multi-scale representation provide a flexible and comprehensive approach to signal analysis that has numerous applications in fields such as signal processing, image analysis, and data compression [29], [30].

TQWT uses a set of filters that are based on wavelet theory to divide a signal into frequency sub-bands. The TQWT can be expressed mathematically as follows:

Let x[n] be the input signal of length N.

The TQWT decomposes x[n] into a set of wavelet coefficients c[n,k] and scaling coefficients d[n,k] at each level k, with k ranging from 0 to K-1. The scaling coefficients of the TQWT technique acquire the low-frequency constituents of the signal, while the wavelet coefficients acquire the high-frequency constituents.

The TQWT can be expressed as:

$$c_{n,k} = (x_n \times \psi_{n,k}) \times \sqrt{2^{k-Q}} \tag{1}$$

$$d[n,k] = (x[n] \cdot \phi[n,k]) \cdot \sqrt{2^k} \tag{2}$$

where $\psi_{n,k}$ and $\phi[n,k]$ are the wavelet and scaling functions, respectively, at level k, and Q is the Q-factor that determines the width of the frequency band that each filter will pass. The * denotes the convolution operation.

The TQWT is typically applied recursively, with each level of the transform dividing the input signal into frequency sub-bands and applying the same set of filters to each sub-band. This process results in a multi-scale representation of the input signal, with the coarsest scale representing the low-frequency constituents and the finest scale representing the high-frequency constituents.

The TQWT can also be used for signal synthesis, i.e., reconstructing the signal from its wavelet and scaling coefficients. The reconstruction can be expressed as:

$$x[n] = \sum_k c[n,k] \cdot \psi[n,k] \cdot \sqrt{2^{k-Q}} + d[n,k] \cdot \phi[n,k] \cdot \sqrt{2^k} \tag{3}$$

The TQWT utilizes re-oversampled filters and real scaling factors. The Q factor, a manipulable parameter, regulates the oscillatory characteristics of wavelets and their level of preservation. The TQWT employs an indeterminate, unbounded range of levels to calculate the r parameter, which achieves redundancy. It is recommended that a value equal to or greater than 3 be assigned to the R parameter. The J parameter determines the count of filter banks utilized in the system and the various scales of the wavelet transform used in the TQWT. The input signal is split into frequency sub-bands using a sequence of filter banks in the transformation process. The TQWT decomposes the input signal into J+1 sub-bands where each sub-band represents a different scale of the signal's frequency components. The sub-band with the lowest frequency harbors the scaling coefficients, whereas the remaining sub-bands entail wavelet coefficients corresponding to diverse scales [30]. The proposed approach experimented with different Q values to achieve optimal classification performance and found that the best results were obtained with Q = 1, r = 3, J = 9. Ten subbands were calculated from each EEG channel. The TQWT method's overall process is presented in Figure 2.

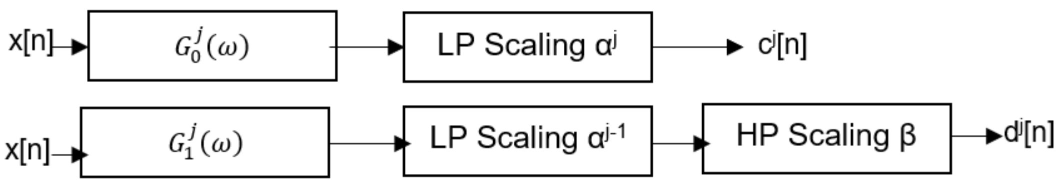

Figure 2. General flow chart of the TQWT method

The computation complexity of TQWT depends on three factors: the number of decomposition levels, the oversampling rate and the filter lengths. As shown in 4, FFTs can be used to implement TQWT efficiently for finite-length signals. The following equation gives the computational cost per sample for analysis and synthesis:

$$C = (2 \log2 N + 2) R / N \tag{4}$$

where N is the signal length, R is the oversampling rate and log2 N is the number of decomposition levels [31].

The TQWT allows the user to adjust the Q-factor, which is the ratio between the center frequency and the bandwidth of the filters utilized in the transformation. By adjusting the Q-factor, it is possible to align the oscillatory behavior of the signal. Additionally, the TQWT uses a real-valued scaling factor and a filter bank that is over-sampled and perfectly reconstructed with real-valued sampling factors.

Calculation of Hjorth Parameters Features and Applying Statistical Tests to These Features

In this section, statistical features important in distinguishing AD controls from healthy controls were extracted from the TQWT subbands. Hjorth parameters were calculated from the subbands obtained by TQWT and extracted as features.

Hjorth parameters are a set of measures commonly used in the field of neuroscience to analyze the time-domain characteristics of electroencephalography (EEG) signals. These parameters were first introduced by Mogens Hjorth [32] in 1970 as a means of quantifying the amount of activity, complexity, and regularity present in EEG signals. The three primary Hjorth parameters are activity, mobility, and complexity. Activity refers to the power or amplitude of the EEG signal and is typically calculated as the variance of the signal over time. The concept of mobility pertains to the speed of signal variation or displacement, which can be quantified by taking the ratio of the standard deviation of the first derivative of the signal to its variance. The term 'complexity' pertains to the non-uniform or non-predictable aspects of a signal and can be measured by computing the ratio between the standard deviation of the second derivative and that of the first derivative of the signal. The Hjorth parameters are useful for characterizing different states of brain activity and have been applied to a wide range of clinical and research applications. For example, they have been used to investigate changes in brain activity during various cognitive tasks, to identify abnormalities in EEG signals associated with neurological disorders, and to assess the effects of pharmacological interventions on brain activity [19]. Overall, the Hjorth parameters provide a valuable tool for researchers and clinicians to quantitatively analyze the characteristics of EEG signals and gain insights into the underlying neural processes that give rise to them.

The distinctiveness of features in relation to the target variable or other features can be assessed by statistical tests that compare their values or distributions. Various statistical measures, such as mean, variance, correlation, etc., are used to compute a test statistic and a p-value. The test statistic quantifies the magnitude of the difference or association between the variables. The p-value indicates the probability of obtaining such a difference or association under the null hypothesis of no effect. A low p-value implies a high level of significance for the difference or association. A high p-value suggests that the difference or association could be attributed to chance. A conventional criterion for significance is 0.05, which corresponds to a 5% probability of rejecting the null hypothesis when it is true. Statistical tests allow for the identification of characteristics that exhibit a high test statistic and a low p-value in relation to either the target variable or other attributes. These features tend to have a robust and stable influence on the performance of the machine-learning model. They also tend to be more informative and less redundant than other features.

The t-Test [33], Wilcoxon rank-sum [34], and Kolmogorov-Smirnov [35] tests, which are widely used in the literature, were utilized to evaluate the discriminatory power of the computed statistical characteristics. The chi (p) values of the Hjorth parameters obtained when these tests were applied are shown in Table 1.

Classification Process

This section evaluates the accuracy of the proposed method by applying SVM, KNN and MLP classifiers, which are widely used as benchmarks in the literature. These classifiers have been chosen for the study because they have been applied to many different biomedical signals for disease diagnosis in the literature. The main rationale for selecting these classifiers is that they achieve high classification metrics with low computational complexity. The KNN algorithm yielded the most superior classification performance when utilized with the proposed approach. The experimental studies provided clear evidence of the chosen classifiers' performance.

Quantifying Model Performance: An Analysis of Evaluation Metrics

In the present study, an assessment of the proposed method's performance was conducted through the utilization of a comprehensive set of nine evaluation metrics. These metrics encompassed the True Positive Rate (TPRate), False Positive Rate (FPRate), Precision, Recall, F-Measure, Matthews Correlation Coefficient (MCC), Receiver Operating Characteristic (ROC) area, Confusion Matrix, and accuracy. To mitigate issues of overfitting and underfitting outcomes in the classification process, a 10-fold Cross Validation approach was implemented. This methodological strategy is particularly advantageous in scenarios where the amount of available data is constrained. The error rate is a pivotal determinant of classifier performance, which is computed by tallying the number of misclassified samples. Conversely, correct classification events are also recorded as a component of classifier performance (Figure 3).

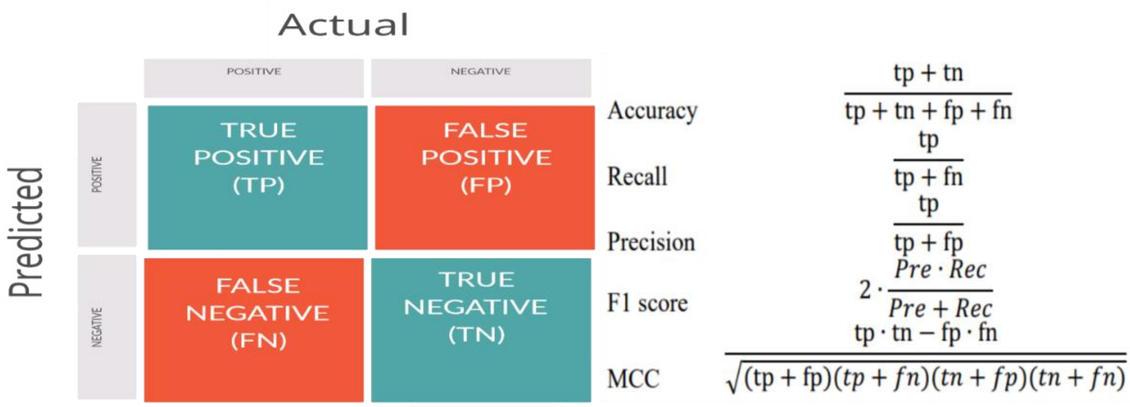

Figure 3. A comprehensive summary of the calculation procedures pertaining to the evaluation criteria that were utilized during the classification process.

3. EXPERIMENTAL RESULTS

Initially, the data from each EEG channel was subjected to the MSPCA method in order to eliminate any noise artefacts present in the signal. Subsequently, the TQWT technique was utilized to partition the signal into subbands, from which statistical features were extracted. In the first phase of the analysis, the distinctiveness of each subband was assessed individually. To this end, three features were extracted from the data of each subject channel, yielding a length vector of 19 channels by 3 features for both AD patients and healthy controls. This process resulted in the generation of a 912x3 matrix, encompassing the total length of all subjects (48 subjects x 19 channels).

To assess the effectiveness of the computed statistical features in discriminating accurately between individuals with AD and those who are healthy, a suite of statistical analysis tests (including the t-Test, Wilcoxon rank sum, and Kolmogorov-Smirnov tests) was employed. The ρ values obtained by subjecting the statistical features extracted from the subbands obtained via the TQWT process to these aforementioned analysis tests are presented in Table 1. Upon examination of Table 1, it becomes apparent that the Hjorth parameters exhibit superior discrimination ability between AD patients and healthy controls across all statistical tests.

Table 1. The p values obtained as a result of the statistical analysis tests of the Hjorth parameters

t-test			Wilcoxon rank-sum			Kolmogorov-Smirnov test		
Activity	Mobility	Complexity	Activity	Mobility	Complexity	Activity	Mobility	Complexity
1.01E-44	1.51E-272	1.04E-266	0.00E+00	7.61E-284	0.00E+00	0	0.00E+00	0
2.27E-91	1.50E-156	7.10E-265	0.00E+00	4.39E-88	1.24E-291	0	7.99E-113	0.00E+00
5.45E-90	1.71E-198	4.42E-262	0.00E+00	1.19E-170	0.00E+00	0	1.35E-220	0
4.99E-61	4.62E-194	1.78E-239	0.00E+00	2.37E-183	0.00E+00	0	3.51E-237	0.00E+00
4.07E-94	3.73E-246	1.49E-218	0.00E+00	8.80E-286	0.00E+00	0	0.00E+00	0.00E+00
1.16E-87	1.22E-269	8.59E-230	0.00E+00	1.58E-299	0.00E+00	0	0.00E+00	0
7.88E-49	2.37E-248	1.09E-238	0.00E+00	1.35E-293	0.00E+00	0	0.00E+00	0.00E+00
1.08E-62	9.76E-239	1.98E-237	0.00E+00	1.97E-287	0.00E+00	0	0	0
4.88E-67	7.96E-250	1.37E-228	0.00E+00	6.96E-297	1.58E-307	0	0	0
1.69E-63	4.74E-268	1.71E-217	0.00E+00	1.48E-282	3.17E-296	0	0	0

Table 2 presents the accuracy values obtained through the classification of features extracted from multiple channels using distinct classifiers. The results demonstrate that the KNN algorithm outperforms the other classifiers in terms of performance. The KNN classifier employed hyperparameters such as k=5, batch size=100, and Euclidean distance. Similarly, the SVM classifier utilized a polynomial kernel with batch size=100 and logistic calibration. The MLP classifier employed batch size=100, and a learning rate of 0.3. All classifiers were subjected to 10-fold cross-validation during classification.

Table 2. The assessment criteria acquired from prominent classifiers' classification of characteristics across all sub-bands via the TQWT technique.

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	Accuracy	
KNN	0.998	0.002	0.998	0.998	0.998	0.996	0.999	99.78	±0.004
SVM	0.995	0.005	0.995	0.995	0.995	0.989	0.995	99.45	±0.005
MLP	0.993	0.007	0.993	0.993	0.993	0.987	1	99.34	±0.006

The evaluation measures resulting from the classification of features extracted from sub-components of the signal, utilizing the TQWT method with parameters Q=1 and J=9, via the KNN classification algorithm, are illustrated in Table 3. The analysis of the table reveals that the SB10 yields the highest classification accuracy, indicating that high-frequency components possess greater discriminative power between AD patients and healthy controls. Moreover, a detailed graphical representation of the evaluation metrics presented in Table 3 is depicted in Figure 4.

Table 3. Evaluation metrics of subbands separated by TQWT using KNN classifier

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	Accuracy	
SB1	0.634	0.366	0.634	0.634	0.634	0.268	0.663	0.64	±0.40
SB2	0.786	0.214	0.787	0.786	0.786	0.574	0.841	0.79	±0.25
SB3	0.795	0.205	0.795	0.795	0.795	0.59	0.859	0.8	±0.24
SB4	0.797	0.203	0.797	0.797	0.797	0.594	0.863	0.8	±0.22
SB5	0.848	0.152	0.855	0.848	0.847	0.702	0.899	0.85	±0.17
SB6	0.833	0.167	0.834	0.833	0.833	0.668	0.887	0.83	±0.20
SB7	0.788	0.212	0.788	0.788	0.788	0.577	0.847	0.79	±0.25
SB8	0.842	0.158	0.842	0.842	0.842	0.684	0.89	0.84	±0.19
SB9	0.938	0.063	0.938	0.938	0.937	0.875	0.958	0.94	±0.08
SB10	0.976	0.024	0.976	0.976	0.976	0.952	0.984	0.98	±0.03
ALL SUBBANDS	0.998	0.002	0.998	0.998	0.998	0.996	0.999	0.99	±0.004

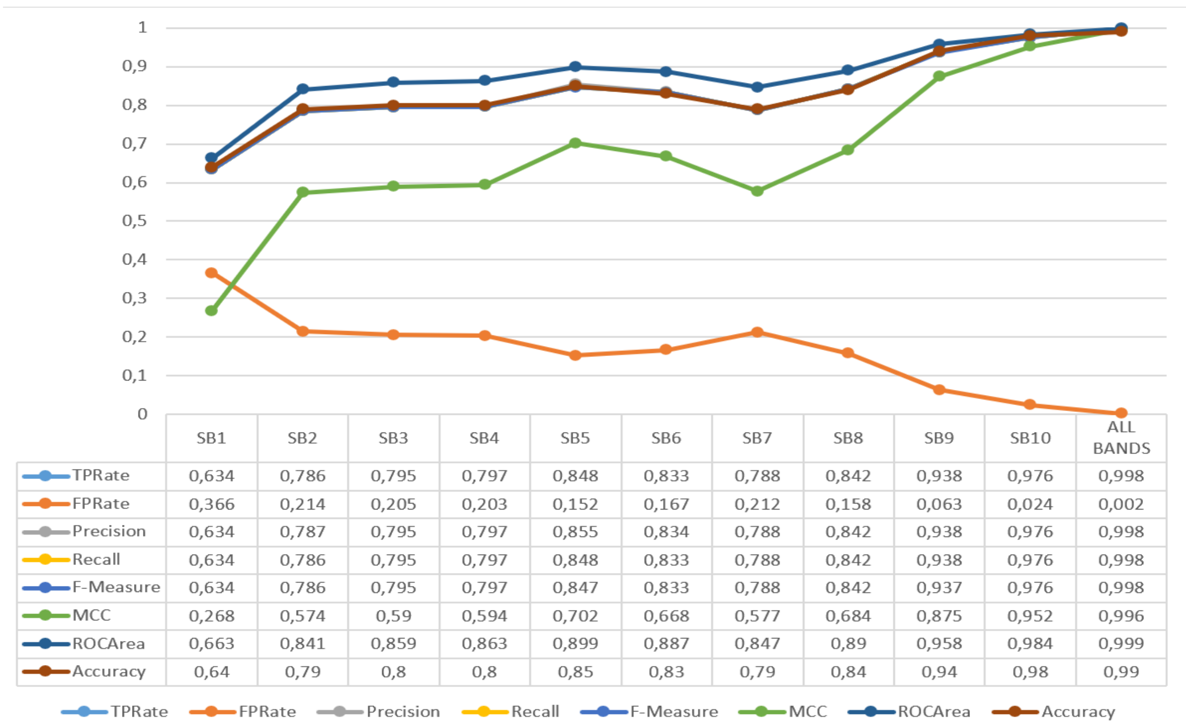

Figure 4. Graphical representation of the evaluation metrics obtained in Table 3

The study presented a novel approach that examined the influence of each electrode data on distinguishing Alzheimer's disease patients from healthy controls. Performance measures obtained through the KNN classifier, which classified features extracted from SB10 sub-component of the TQWT method for each electrode, are presented in Table 4. Results showed a high impact of each electrode data on classification, with minor variations between some electrodes.

Particularly, satisfactory classification performance was achieved by the P3 and P4 channels.

Table 4. The assessment criteria based on electrodes acquired through the classification of features from SB10 using the KNN classifier

		TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	Accuracy	
1	**Fp1**	0.88	0.13	0.88	0.88	0.88	0.75	0.94	0.88	±0.13
2	**Fp2**	0.92	0.08	0.92	0.92	0.92	0.84	0.97	0.92	±0.09
3	**Fz**	0.96	0.04	0.96	0.96	0.96	0.92	0.98	0.96	±0.07
4	**F3**	0.94	0.06	0.94	0.94	0.94	0.88	0.98	0.94	±0.05
5	**F4**	0.98	0.02	0.98	0.98	0.98	0.96	0.99	0.98	±0.05
6	**F7**	0.92	0.08	0.92	0.92	0.92	0.84	0.99	0.92	±0.08
7	**F8**	0.88	0.13	0.88	0.88	0.88	0.75	0.94	0.88	±0.14
8	**Cz**	0.96	0.04	0.96	0.96	0.96	0.92	0.99	0.96	±0.05
9	**C3**	0.98	0.02	0.98	0.98	0.98	0.96	0.98	0.98	±0.04
10	**C4**	0.98	0.02	0.98	0.98	0.98	0.96	0.98	0.98	±0.04
11	**T3**	0.94	0.06	0.94	0.94	0.94	0.88	0.98	0.94	±0.07
12	**T4**	0.90	0.10	0.90	0.90	0.90	0.80	0.88	0.90	±0.11
13	**Pz**	0.98	0.02	0.98	0.98	0.98	0.96	0.98	0.98	±0.05
14	**P3**	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	±0.02
15	**P4**	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	±0.03
16	**T5**	0.98	0.02	0.98	0.98	0.98	0.96	1.00	0.98	±0.03
17	**T6**	0.98	0.02	0.98	0.98	0.98	0.96	0.99	0.98	±0.04
18	**O1**	0.98	0.02	0.98	0.98	0.98	0.96	0.98	0.98	±0.04
19	**O2**	0.96	0.04	0.96	0.96	0.96	0.92	0.98	0.96	±0.06
	All Channels	0.998	0.002	0.998	0.998	0.998	0.996	0.999	0.99	±0.004

The classification accuracies of extracted features from subbands obtained through various decomposition methods and classified using different algorithms are presented in Table 5. The results reveal that the proposed method achieves the highest classification performance. Furthermore, upon examination of the table's total working time area, it is evident that the proposed method offers significant computational advantages over alternative methods. Additionally, the table provides information on the number of features obtained from subbands and the number of subbands utilized. The classification performance metrics obtained in Table 5 are graphically shown in Figure 5.

Table 5. The accuracy values acquired through the classification of features extracted from all sub-bands of data collected from diverse channels utilizing distinct decomposition methodologies.

	KNN	SVM	MLP	Total run time (second)	Number of subbands	Number of Features
VMD	97.04±0.03	96.05±0.04	97.04±0.04	154.864698	5	15
EMD	85.52±0.15	88.37±0.12	91.88±0.09	5.015938	5	15
EWT	96.60±0.04	88.60±0.11	95.61±0.06	4.227603	2	6
EEMD	85.53±0.15	88.38±0.12	91.88±0.09	33.080941	5	15
MVMD	70.94±0.29	74.01±0.26	74.45±0.30	234.266445	6	18
TQWT	99.78±0.004	99.45±0.005	99.34±0.006	2.357646	10	30

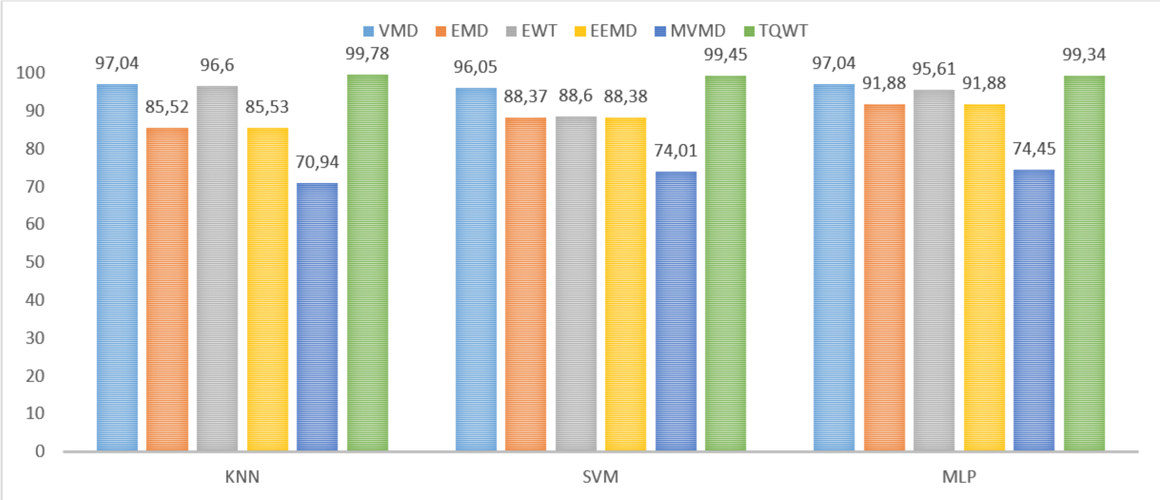

Figure 5. Classification accuracy obtained by the proposed methodology and classification of different decomposition methods.

Table 6 presents the accuracy results of feature-based classification using distinct classifiers, where the features are computed across all subbands derived from the TQWT method with different Q values. The analysis reveals that the optimal classification performance is achieved at Q=1.

Table 6. Accuracy values obtained by classifying the extracted features from all bands and channels for various Q values.

	Q=1	Q=2	Q=3
KNN	99.78	99.12	97.03
SVM	99.45	98.79	97.80
MLP	99.34	98.35	98.57

Figure 6 presents the proposed method and complexity matrices of various decomposition methods, demonstrating their high performance in distinguishing AD patients and healthy controls, particularly with the proposed method. Upon examination of the figure, it is evident that the proposed method successfully distinguishes all healthy individuals, with only two AD patients being incorrectly detected. These results unequivocally demonstrate the efficacy of the proposed method. Additionally, Figure 7 displays the ROC curves of the Confusion Matrices.

EMD	HC	AD
HC	384	72
AD	60	396

EEMD	HC	AD
HC	384	72
AD	60	396

EWT	HC	AD
HC	439	17
AD	14	442

MVMD	HC	AD
HC	325	131
AD	134	322

TQWT	HC	AD
HC	456	0
AD	2	454

VMD	HC	AD
HC	443	13
AD	14	442

(Columns: Prediction; rows: Actual)

Figure 6. Complexity matrices obtained by applying the proposed method to different decomposition methods

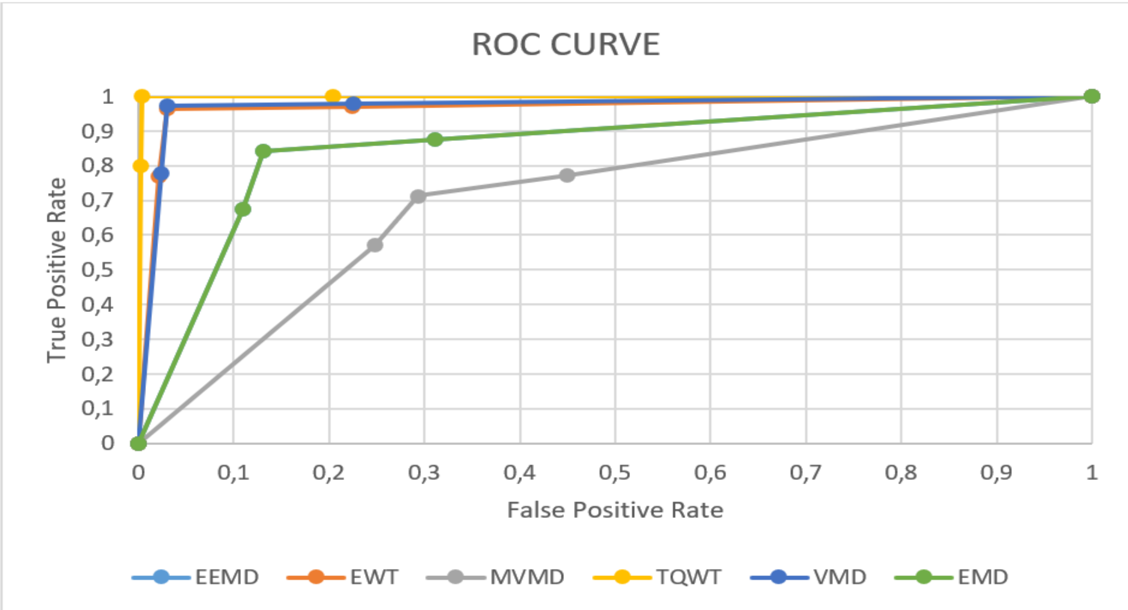

Figure 7. ROC curves obtained by applying the proposed method to different separation methods

4. DISCUSSIONS

Advancements in the healthcare industry have facilitated a healthier and extended lifespan for the global populace. Nonetheless, the surge in the incidence of unwarranted maladies like dementia leads to unfavourable outcomes [5], [6], [36]–[38]. Despite the lack of a definitive cure for Alzheimer's disease, timely detection of the ailment can decelerate its progression and augment the standard of living of the affected individuals [39]. The process of diagnosing the disease necessitates the undertaking of multiple medical procedures, including neurological and psychiatric evaluations, blood analyses, and computed tomography, which should be thoroughly assessed by an expert in a comprehensive manner [40]. Moreover, notwithstanding the intricate diagnostic procedures, it has been reported that even proficient specialists encounter misdiagnosis in a range of 10-15% of instances [38], [41]. Given these considerations, the development of computer-aided diagnosis (CAD) systems utilizing solely biomedical signals or images is imperative. While biomedical imaging techniques (e.g. CT, fMRI, PET) entail high costs and time commitments, the lower expenses and time requirements associated with EEG signals have rendered them a preferred approach in our research. Table 2 presents an overview of relevant literature studies that have employed EEG signals for the diagnosis of Alzheimer's disease.

In their research, Kulkarni et. al. Utilized SVM as a classifier to analyze various feature values derived from EEG signals for the purpose of Alzheimer’s disease diagnosis [4]. The researchers achieved a 96% classification accuracy for the most complex features in their study. Bairagi performed a classification of distinct feature values utilizing SVM and KNN classifiers in a separate investigation [1]. The researchers achieved the best results in their investigation by utilizing an SVM classifier to classify spectral features that were computed at a success rate of 94%. The study proposed by Ruiz-Gómez et al. incorporated various feature values and evaluated their performance using different classification techniques [5]. By means of the method suggested herein, the authors accomplished a 78.43% rate of success in classification, employing both the MLP and Quadratic Discriminant Analysis (QDA) algorithms. Amezquita-Sanchez et al. conducted a separate investigation in which they employed the EPNN classifier to identify a disease with the highest accuracy of 90.2%. To achieve this, they utilized signal analysis techniques in their method, which they called MUSIC-EWT, and computed Hurst exponent measures and fractal dimension features [6]. Kulkarni was able to discriminate Alzheimer's disease patients and healthy controls with an accuracy of 94% by integrating spectral and complexity features derived from EEG signals and employing the KNN algorithm for classification, as reported in a separate investigation [7]. In their research, Tzimourta et al. employed the Random Forest algorithm to classify statistical and spectral features, which resulted in the highest classification performance of 88.79% [8].

The TQWT method and Hjorth parameters have been widely utilized in the time-frequency analysis of EEG signals due to their superior signal analysis capabilities, as documented in the literature. This study introduces a CAD system that utilizes the TQWT method and Hjorth parameters in tandem, demonstrating high accuracy in distinguishing Alzheimer's patients from healthy controls using EEG signals. Notably, the machine learning-based approach employed in this study has not yet been utilized in previous studies with this particular dataset, thus precluding direct comparisons. Furthermore, the proposed method exhibits high classification performance as well as computational efficiency. Table 7 presents the comparison report of the relevant literature studies.

Table 7. Comparative analysis of the proposed approach vis-à-vis other relevant studies in the literature

	Classifier	Dataset	Feature Extraction	Accuracy
Kulkarni et.al. [4]	SVM	50 Control +50 AD	Complexity features	96%
Bairagi [1]	SVM	50 Control +50 AD	Spectral features	94%
Ruiz-Gómez et.al. [5]	MLP	(37 Control +37 mild cognitive impairment) + 37 AD	Spectral and nonlinear features	78.43%
Amezquita-sanchez et.al.[6]	EPPN	37 mild cognitive impairment + 37 AD	Hurst exponents and fractal dimension	90.3%
Kulkarni [7]	KNN	50 Control +50 AD	Spectral and complexity features	94%
Tzimourta et.al.[8]	Random Forest	10 Control + 8 mild Alzheimer's +6 moderate Alzheimer's	Statistical and spectral properties	88.79%
This Study	**KNN**	**24 Control + 24 AD**	**TQWT technique and Hjorth parameters**	**99.78%**

5. CONCLUSIONS

The objective of this study was to develop a decision support system for discriminating between healthy individuals and those with Alzheimer's disease by utilizing the TQWT and Hjorth methods. The main rationale behind this work is the widespread usage of both methods in the existing literature and their ability to provide superior performance with minimal computational complexity.

Moreover, our proposed methodology encompasses electrode-based evaluation and comparative analysis of different separation methods. Traditional methods for diagnosing Alzheimer's disease involve expensive tests that are time-consuming and require evaluation by a specialist. In addition, the evaluation process is often influenced by the clinician's professional experience, leading to inconsistent outcomes in some cases. As a result, we have developed a machine-learning model using the proposed methodology to detect the disease. The presented method achieved high classification performance and yielded satisfactory results, which could supplement expert opinions in differentiating between Alzheimer's patients and healthy controls.

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