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Alzheimer Disorders Diagnosis System Design using Machine Learning for EEG Signal

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Abstract

The diagnosis of Alzheimer's disorders (AD), a prevalent neurological disorder, can created by utilising a range of therapeutic methods, including the electroencephalogram (EEG), which has been especially successful in the past. The objective for this study is to develop a computer-aided diagnosis tool which may recognize AD from EEG data. The EEG information was cleaned up with a band-pass elliptic digital filter to remove any interference or disruptions. The filtered signal was then divided into its frequency ranges using the Discrete Wavelet Transform (DWT) method, enabling the extraction of EEG signal characteristics. To enhance the diagnostic performance, various signal features were integrated into the DWT technique, including logarithmic band power (LBP), standard deviation, and root mean square (RMS). These features were incorporated to generate feature vectors that were utilized in the diagnosis process. In order to categorize the EEG features into their respective classes, various machine learning (ML) approaches were explored, including quadratic discriminant analysis (QDA), support vector machine (SVM), and k-nearest neighbour (KNN). The performance of these approaches was then evaluated by comparing and computing their sensitivity, specificity, and overall diagnosis accuracy. When comparing the accuracy values, it can be observed that QDA has a higher accuracy of 97.5% compared to KNN's accuracy of 95%.

Keywords: Alzheimer's Disease, Electroencephalogram, Discrete Wavelet Transform, Logarithmic Band Power, Machine Learning.

INTRODUCTION

A large number of individuals around the globe are affected by the neurodegenerative ailment known as AD, especially the elderly, leading to cognitive impairment and memory loss. Early diagnosis is crucial to intervene promptly and improve patient outcomes. Pathologically, various neurodegenerative disorders, including AD, are characterized by a typical amyloid generation, impaired clearance, aggregation, and folding [1]. Among the world's top causes of death, AD is a common and complex neurodegenerative condition that imposes substantial direct and external expenses on families and communities. The start of AD typically happens after the age of 65 and is uncommon in younger people. Age is biggest risk factor for getting AD because likelihood of this sickness rises with age [2]. Early diagnosing criteria omitted individuals with progressive dementia in order to officially recognize AD as a separate disease. This was because senile dementia was common and often considered a natural part of the aging process, rather than a genuine disease [3].

EEG is non-invasive and cost-effective technique that provides valuable information on brain activity and holds promise in the diagnosis of AD. It has the ability to be a useful diagnostic device for

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conditions of the central nervous system and detects electrical activity neurons in the brain. Epilepsy is presently diagnosed using EEG throughout the world's healthcare institutions. Research had been initially spurred through the correlation between AD and epilepsy activity, despite the fact that they have had only modest success in identifying AD using epileptiform activity in EEG [4]. The electrical signals recorded in EEG are generated by postsynaptic potentials of pyramidal neurons, which are most abundant type of neurons in the cerebral cortex. The synchronized activity of these neurons produces detectable electrical potentials can measured on scalp surface using EEG electrodes. EEG signals reflect the ongoing brain activity and can provide insights into the functional and cognitive states of the brain. The non-invasive nature of EEG and its ability to capture real-time brain activity make it an attractive tool for diagnosing and monitoring neurological disorders [5]. The EEG method was widely used between researchers and clinicians because it is comparatively straightforward to use. It is feasible to record shifts in cortex electrical activity from a variety of brain areas using just two electrodes placed on the scalp. Accordingly, choosing a particular electrode configuration is not essential as long as the desired alterations in brain function can be found at the head. EEG is a flexible and trustworthy technique for non-invasively detecting brain function as a result [6].

Recent years have seen researchers increasingly turned to ML algorithms analyse EEG signals and develop diagnostic systems for AD. ML algorithms have proven effective at extracting features from EEG data and identifying patterns that can differentiate individuals with AD from healthy individuals. However, developing a precise and reliable diagnostic system for AD using EEG signals is still challenging due to the complexity of the data and the variability of AD symptoms. DL and ML models have successful in various areas of medical image analysis, including mammography, ultrasound, microscopy, MRI, and others. Deep learning models have demonstrated impressive results in classifying and detecting various diseases affecting different organs, such as the heart, lung, brain, retina, breast, and bone. However, there has been limited research on use of DL models for the detection of AD. Further study has become required to explore potential DL models detecting AD using EEG signals. With the advent of larger datasets and more advanced deep learning models, it is possible that these techniques could become an effective earlier tool and diagnosis of AD. But, it essential to ensure that these models are accurate, reliable, and ethically sound before they can be widely adopted in clinical practice [7].

To control and handle AD effectively, it is essential to identify it in its initial stages of moderate cognitive impairment (MCI). Researchers have suggested using EEG signal processing as a possible way to find indicators and characteristics could aid in AD diagnosis, allowing medical workers to avoid misunderstanding and offer prompt and effective treatment choices [8]. In cases where EEG recordings are lengthy, manual review can be a time-consuming process then is also prone to errors due to presence signal artifacts. Therefore, researchers are exploring automated methods that combine EEG signal analysis with supervised machine learning to aid clinicians in early AD detection, which is a challenging task [9].

The evaluation stage of AD is crucial effective treatment and healthcare, and selecting the appropriate clinical diagnosis system is of utmost importance. Many studies have focused on removing characteristics and putting them into the appropriate groups. Though, no study yet identified a suitable combination method for decomposing EEG signals, extracting structures, and accurately classifying them to develop a reliable clinical diagnosis system for AD. Provide a thorough analysis of the state-of-the-art in creation from ML-based AD diagnostics using EEG data in this article. Discuss the various ML algorithms that have been used, the different features extracted from EEG signals, and performance metrics used toward evaluate the accuracy of these systems. Also highlight the challenges and limitations of current approaches and identify research future directions. The paper is organized as follows: Section 2 presents summary of earlier studies on ADD method for EEG signal. Section 3 discussed about problem statement. The suggested ADD method for EEG signal is introduced in Section 4. Section 5 presents the testing findings and their interpretation. Section 6 brings the paper to a conclusion.

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RELATED WORKS

In their study, Feng et al. [10] introduced the idea of deep learning (DL) and how it has significantly improved image identification when employing MRI and PET to diagnose AD. nevertheless has proven difficult to use CNNs in this situation successfully due to the restricted supply of such imaging data. They suggested a new deep learning framework to get around this restriction by combining the advantages of FSBi-LSTM and 3D-CNN. Their method includes extracting deep feature representations from PET and MRI data using a 3D-CNN framework, and then applying FSBi-LSTM to the deep feature maps' latent spatial information to improve the performance of their model.

In their study, Ramzan et al. [11] proposed SMC, MCI, CN, EMCI, LMCI, and AD are included in multi-class categorization of AD, so it is important to investigate how well rs-fMRI performs in these phases. The research makes use of 138 participants in the AD Brain Imaging Initiative's continuous sample of resting-state fMRIThe researchers conduct a thorough analysis of the ResNet-18 design and consider TL without and with fine-tuning using an expanded system structure, as well as rebuilding the network using a single-channel input from beginning. They execute the job of AD classification using residual neural networks and contrast their findings to earlier studies in this area, offering insights into DL techniques and their applications to AD classification.

Puente-Castro et al. [12] proposed of sagittal MRIs from ADNI and OASIS datasets for AD diagnosis was suggested, and to improve accuracy, Transfer Learning (TL) techniques were employed. Their findings suggest that AD-related damages can be identified in sagittal MRI and DL models using MRIs provide results similar to those obtained from horizontal-plane MRI, which is considered state-of-the-art. This study highlights potential sagittal-plane MRIs for detecting AD at an early stage, which might provide an opportunity for more exploration. It is also important to note that data acquisition in certain fields can be costly.

Amezquita-Sanchez et al. [13] proposed a new method for differentiating between Mild Cognitive Impairment (MCI) and Alzheimer's Disease (AD). This technique integrates signal analysis technique called the Multiple Signal Classification and Empirical Wavelet Transform (MUSIC-EWT), nonlinear characteristics likes the Fractality Dimension (FD) based on Chaos Theory, and a classification algorithm called Improved Likelihood Neural Network Model, which uses EEG signals. Several measures of self-similarity of the signals will be investigated, including the Box Dimension (BD), Higuchi's Fractality Dimension (HFD), Katz's Fractality Dimension (KFD), and the Hurst Exponent (HE). The 37 MCI patients as well as 37 AD patients recorded EEG data were used to confirm the proposed technique's accuracy.

AlSharabi et al. [14] proposed to utilizing EEG data, create a computer-aided AD diagnostic method. An elliptic digital filter was applied to the EEG dataset to remove any interference and disturbances, and the resulting signal was decomposed into its frequency bands using the DWT technique to extract signal features. The extracted features included LBP, average energy, variance, kurtosis, standard deviation, RMS, and Norm, which were integrated to DWT technique toward generate feature vectors that improved the diagnosis performance. Nine different machine learning approaches were evaluated for classifying the EEG features into their corresponding classes, Naive Bayes (NB), including Linear Discriminant Analysis (LDA), Artificial Neural Network (ANN), QDA, SVM, Extreme Learning Machine (ELM), KNN, Decision Tree (DT), and Random Forests (RF). The study aimed to explore the potential as for these machine learning techniques for accurately diagnosing AD using EEG data. Table 1 below provides a comparison of the results obtained using these techniques on AD diagnosis.

Table 1. Existing literatures of research on add

Author	**Method**	**Merit**	**Demerit**
Feng et al. [10]	FSBi-LSTM	By utilizing CNN for label identification, the method in question outperforms other competitive methods.	It is limited by the specific imaging techniques used (MRI and PET) and may not generalize to other imaging modalities or diagnostic contexts.

Ramzan et al. [11]	rs-fMRI	contributes to the ongoing efforts to develop accurate and efficient diagnostic tools for AD, which could ultimately lead to earlier detection and better treatment outcomes.	This research does not provide a detailed analysis of the interpretability and explainability of their approach
Puente-Castro et al. [12]	Transfer Learning (TL)	potentially reduce the cost of obtaining data for a data set.	This research only focused on sagittal-plane MRI data, which may not be widely available or commonly used in clinical settings, limiting the practical applicability of the findings.
Amezquita-Sanchez et al. [13]	MUSIC-EWT	It offers a non-invasive and cost-effective method for diagnosing MCI and AD.	The accuracy of the diagnosis may be affected by quality of EEG data, as well as factors such as patient movement and electrode placement.
AlSharabi et al. [14]	DWT, kurtosis, LBP, standard deviation, average energy, variance, RMS, and Norm.	EEG signals are easy to obtain and do not require expensive equipment or invasive procedures.	It has only been tested on a relatively small sample size, and it may not be generalizable to other populations.

PROBLEM STATEMENT

The problem statement of work is developing a ML-based system for EEG patterns are used to diagnose AD. AD remains a neurodegenerative disease that is difficult to diagnose in its early stages, and current diagnostic methods are often invasive and expensive. EEG signals are non-invasive and easy to obtain, but their analysis requires expertise and is time-consuming. Therefore, the development of an automated system that can accurately diagnose AD using EEG signals can greatly benefit patients and healthcare providers by enabling early detection and treatment of disease. The objective of the work is design machine learning-based ADD system that can accurately differentiate between healthy individuals and those with AD based on their EEG signals.

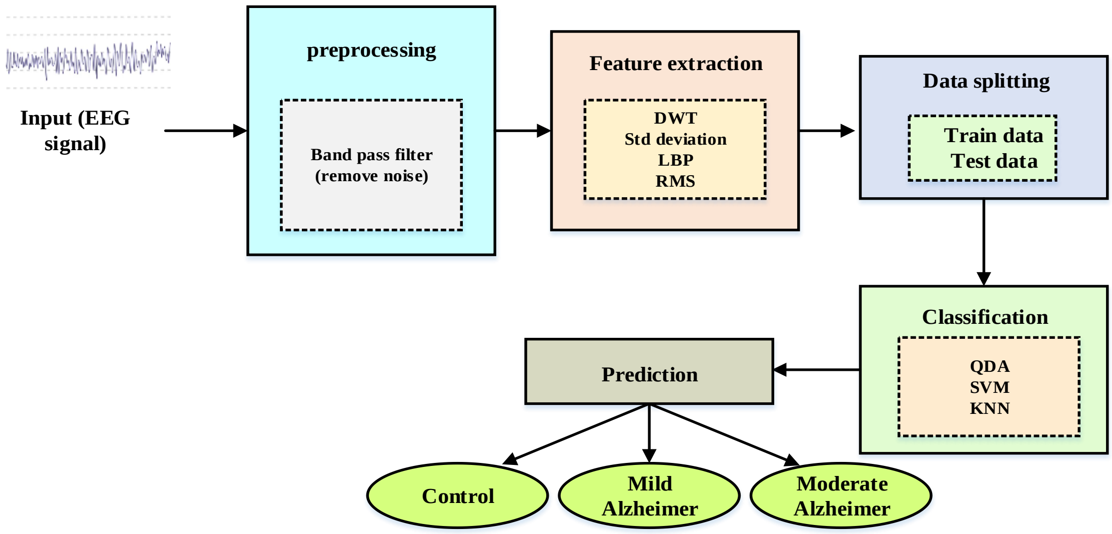

Figure 1. Flow diagram for ADD system design using ML for EEG signal.

PROPOSED ALZHEIMER DISORDERS DIAGNOSIS (ADD) FOR EEG SIGNAL

A conventional EEG device is going to be used to collect EEG data on AD patients and healthy people. Noise and bandpass filters will remove from obtained EEG data during pre-processing. To derive features, the pre-processed EEG data be used. Then will derive a variety of features, including DWT, standard deviation, LBP, and RMS features. will These characteristics will be chosen in order to distinguish AD sufferers from fit people. The collected characteristics will be used to create various ML models, such as SVM, KNN, and QDA. On a dataset, the created models' efficacy will be measured. The effectiveness of the suggested method will be assessed using a variety of performance measures, including accuracy, sensitivity, and specificity. The flow diagram for the design of an ADD system using ML for EEG data is shown below Figure 1.

Input data

Electroencephalography (EEG) is a highly effective method for capturing brain activity from the surface of the scalp, which is classified into delta, theta, alpha, beta, and gamma frequencies ranging from 0.1 Hz to over 100 Hz. Data selection involves the process of selecting the appropriate input signals for distinguishing between pathological and non-pathological states.

The scientific world has free and open access to substantial physiological data datasets through the platform known as PhysioNet. A comprehensive range of physiological signals, including ECG, EEG, blood pressure, respiration rate, and other vital signs, are included in the PhysioNet collection. Researchers regularly utilise this dataset, which has been curated over many years, to create and test machine learning algorithms and other analytical tools. The PhysioNet dataset is made up of many data sets. For instance, the PhysioBank collection includes a range of waveform recordings and clinical and physiological data. The MIT-BIH Arrhythmia database, which contains more than 30 hours of ECG recordings from people with various arrhythmias, is one of the most often used datasets on the PhysioNet platform. For researchers looking to create and assess algorithms for clinical decision support, physiological signal analysis, and other relevant applications, the PhysioNet dataset is a valuable resource.

Data splitting: The cross-validation was used in the classification method, where EEG features were arbitrarily divided into subgroups, one of which was reserved for testing (validation), and the other subsets were employed for training. Until each subgroup had been tested once, this procedure was repeated. From a feature array created using the feature extraction methods, the EEG features were extracted. 90% of the characteristics were used for teaching and 10% were used for testing. The classifier was trained using the training subgroup, and an arrangement was created and stored. The trained classifier was subsequently fed the tested subgroup, and the output was contrasted with the initial test features to ensure accuracy.

Pre-processing

Band pass filter for noise removal: During EEG data recording, various artifacts, noises, and interferences are inevitably captured alongside brain signals. These disturbances can originate from various sources, including electrodes, electronic devices' magnetic fields, blood pressure, eye blinking, limb movements, breathing, or other human actions. In pre-processing stage, a band-pass filter has been applied EEG signals to eliminate interferences and noises that occurred during recording. This step is crucial to ensure that only meaningful brain signals are analyzed and interpreted, free from unwanted disturbances.

In signal processing, band-pass filtering is used to isolate and extract specific frequency bands from a signal of interest. In the case of EEG signals, band-pass filtering is used to extract frequency bands corresponding to brain activity while suppressing noise and artifacts. To prevent the distortion or alteration of diagnostic interpretation of EEG signals during band-pass filtering, it is recommended to use a high-pass filter by a low cut-off frequency of 0.05 Hz and a low-pass filter with a high cut-off frequency of 150 Hz. This filter setup allows for the display of the maximum available frequency bandwidth in the EEG signal while eliminating unwanted noise and artifacts. An electrical component or circuit known as a band-pass filter enables signals within a particular frequency band to flow through while preventing or reducing signals at different frequencies. The filter is designed to have a response that is relatively flat within the passband (i.e., the desired frequency range) and a steep roll-off outside the passband to minimize interference from signals outside the desired range. The specific parameters of the band-pass filter (e.g., cut-off frequencies, filter type, filter order) depend on the EEG recording setup and the research or diagnostic question of interest.

Feature Extraction

Feature extraction is an essential step in signal's processing manipulate, especially when working with biological data like EEG. Firstly, it enables reduction dataset resources without losing important information, thereby decreasing dimensionality by eliminating redundant data. This, in turn, allows for the creation of a model with less computational effort, thereby increasing speed of training and learning while improving accuracy of modelled learning. Additionally, feature extraction reduces the risk of overfitting and improves data visualization.

Various techniques are available for feature extraction in EEG signal analysis. One commonly used technique is DWT, which suitable for analyzing non-stationary and non-linear signals with varying resolutions and frequencies. By breaking down EEG signals toward various functions employing a singular operate known as the mother function, DWT examines signal features in both frequency and time domain. By applying DWT, important features of EEG signals can be extracted and used for various applications, including classification, clustering, and prediction. The specific features extracted depend on the research or diagnostic question of interest. Overall, feature extraction is a critical step in EEG signal processing, enabling the extraction of important information from complex and noisy signals in Eq.1.

$$\psi(T) = \frac{1}{\sqrt{2}}\psi\left(\frac{T-b}{a}\right) \quad a, b \, \epsilon sp, a > 0 \tag{1}$$

The scaling and shifting parameters are denoted by 'a' and 'b', respectively, and sp represents space of wavelet. This equation illustrates how the wavelet transform decomposes a signal into its constituent wavelets by convolving the signal with a set of scaled and shifted versions of a wavelet function ψ of Eq.2.

$$F(a,b) = \frac{1}{\sqrt{a}}\int \psi(\frac{T-b}{a})\, dt \tag{2}$$

DWT has been utilized in the current study due to its capability of providing a highly efficient representation of the signal. This is demonstrated by the following equation. The filtered EEG signal takes subjected to DWT, which decomposes the signal into high pass and low pass filters, obtaining an approximation and detail coefficients as a representation of the signal in the first level Eq.3.

$$F(T) = \sum_{K=-\infty}^{K=+\infty} W_{n,K}\ \phi(2^{-n}\, T - K)\ + \sum_{K=-\infty}^{K=+\infty}\sum_{K=-\infty}^{K=+\infty} 2^{\frac{-j}{2}}\, Z_{j,K}\psi(2^{-j}\, T - K) \tag{3}$$

The wavelet decomposition process involves decomposing a signal into different frequency bands using a set of wavelet functions. In this process, the signal is repeatedly decomposed its detail and approximation coefficients at different levels. The coefficients approximation at one level become the input for the next level. The signal is decomposed into approximation coefficients at each level of the process ($Z_{j,K}$) and detail coefficients ($W_{n,K}$), where n represents level and ψ is wavelet function. The approximation coefficients from previous level (A1) are used as input for the second level, where they are decomposed into new approximation coefficients (Z2) and detail coefficients (W2). This process is repeated until final level (n), where the approximation coefficients (Zn) and detail coefficients (Wn) are obtained. This process allows for a multiresolution analysis of the signal, with each level representing a different level of detail in the signal.

DWT was used in the present study to produce an effective approximation of the EEG data. The mother wavelet function and the total amount of segmentation levels are key factors in the DWT breakdown of the signal into estimates and detail components at various levels. In this study, the mother wavelet function was Daubechies 4 (db4), and there were four layers of segmentation. DWT was mixed with different mathematical characteristics like power LBP, and standard deviation in order to increase the diagnostic system's effectiveness. Nevertheless, for non-stationary and non-linear signals, like EEG data, conventional statistical characteristics are typically ineffective. Other characteristics that might more accurately characterize the dispersion of power and information for

EEG data were therefore looked across. The feature vectors were subsequently constructed using these characteristics. For each individual in each of the three groups, DWT was merged with a single statistical characteristic, and the results were compared and assessed. Mean and standard deviation are insufficient statistical characteristics for non-stationary and non-linear data, such as EEG signals. Because these features do not effectively represent the qualities of such signals, they are not appropriate for quantifying complicated data. This is particularly true for finite signals with N examples, such as sig(n), where n is a positive integer between 1 and N, and a mean and standard deviation. Finally, precise classification of these characteristics using machine learning techniques enhanced the efficacy of the diagnostic system showed in Eq.4,5,6.

Standard deviation (StndDev)

$$StndDev = \sqrt{\frac{1}{N}\sum_{n-1}^{N}(\mathrm{sig(n)} - \mu)^2} \tag{4}$$

Logarithmic band power (lpb)

$$lpb = \log(\frac{1}{N}\sum_{n=1}^{N}|sig(n)|^2) \tag{5}$$

Root means square (rms)

$$\mathrm{rms} = \sqrt{\frac{\sum_{\mathrm{n=1}}^{\mathrm{N}}|\mathrm{sig(n)}|^2}{N}} \tag{6}$$

It is essential to report the count of feature vectors obtained during the feature extraction process for each dataset category, namely Control, Mild AD, and Moderate AD. This information helps in understanding the dimensionality of the feature space and level in complexity of data of each category.

Classification

In order to evaluate performance in diagnostic system, several metrics such classifier accuracy, sensitivity, and specificity can be used. To achieve the best possible classification accuracy, various classifiers including QDA, SVM, and KNN have been utilized and assessed in this research. The machine learning models have carefully tuned by selecting appropriate operating parameters. However, the learning rate parameter is a critical factor ML approaches can be significantly affected by various factors that may impact their performance. A very high learning rate can cause the models to skip optimal performance, whereas a very low learning rate may lead to the models never converging because of the extreme effort to find the exact optimal performance.

SVM: A characteristic hyperplane is used by SVM classifier to determine classes [15]. The hyper plane that maximizes the margin, or the separation from the closest training points, is the one with the highest resolution that is chosen. The ability to generalize is known to enhance when the margin is maximized. It is a quadratic optimization problem to train the SVM in Eq.7,8.

$$f(d) = sign[X(d)] \tag{7}$$

$$X(d) = \sum_{i=1}^{\#SV}\alpha_i a_i\left(d, d^{SV}{}_i\right) + z \tag{8}$$

here #SV is the number of support vectors, i is the nonnegative Lagrange multipliers, $X(d)$ is the signed distancing function for evaluating classification trust, and z is an offset parameter. The support vectors depicted the data points $d^{SV}{}_i$ matching with i > 0. SVM provided an effective tool for dynamic classification with an extremely nonlinear decision boundary by using the right kernels. Until now, the Gaussian or radial basis function (RBF) kernel has been the most often utilized in Eq.9.

$$K(d,d_i)=\exp\left(\frac{\|d-d_i\|^2}{2\sigma^2}\right) \tag{9}$$

KNN: Given that it is one of the most basic algorithms for machine learning, the k-NN is one of the most often used classification methods. The k-NN approach is non-parametric. Based on the closest training characteristics, this algorithm categorizes the extracted important features. During the training set, it seeks to categorize an unlabeled input for its k-NN. The k-NN classifier's k variable, which is crucial, should be properly chosen. In this research, k = 1 is chosen as the number of neighbors. A particular information point is classified using the KNN classifier, a non-parametric method, based on the vast majority of its neighbors [16]. The KNN algorithm accomplishes its execution in two steps: first determining the number of closest neighbors, then utilizing the results of the first step, categorizing the data point into a certain class. It uses distance metrics like Euclidean distance, as provided in equation, to determine the neighbor in Eq.10.

$$distance(p,q)=\sqrt{\sum_a \left(p_a-q_a\right)^2} \tag{10}$$

QDA: A popular supervised classification technique, the QDA is closely connected to a linear discrimination analysis. The QDA utilizes a straightforward max gate function as a classification criterion and assumes that the covariance matrix might differ for each class [17]. The QDA's equation is shown below Eq.11:

$$v_i(D)=-\frac{1}{2}\left(D-\mu_i\right)^H Cov_i^{-1}(D-\mu_i)+\log \pi_i \tag{11}$$

When D belongs to class i, stands for the mean value of every class, H is a transposition operator, and Cov_i^{-1} is the i th class's covariance matrix.

RESULT AND DISCUSSION

The effectiveness and reliability of a suggested technique can be determined by using performance criteria such as accuracy, specificity, and sensitivity. For model deployment, the Raspberry Pi 3B module was used. This mini central processing unit is capable of working with various programming software such as C, Embedded C, C++, Python, and Java. The Raspberry Pi 3B model is a third-generation single-board computer that is powerful and compact, making it suitable for various applications. It is equipped with a Broadcom BCM2387 chipset that features a 1.2 GHz Quad-core ARM Cortex-A53 64-bit processor, as well as 802.11 Bluetooth 4.1 and wireless LAN connectivity. Memory of the Raspberry Pi 3B is 1 GB LPDDR2 (SDRAM), which is a low-power double data rate memory. The operating system used is the Raspbian OS, which is a Linux-based operating system that boots from a micro-SD card. With its additional features, including wireless LAN, Bluetooth connectivity, and Wi-Fi, the Raspberry Pi 3B is an ideal solution for a powerful connected design. Furthermore, this model is ten times faster than the first-generation Raspberry Pi, making it a more powerful option.

The band-pass IIR elliptic digital filter was used to remove noise and interference from the EEG samples in order to increase the signal-to-noise level. EEG is a useful method that serves to collect brain impulses related to different conditions from the surface of the scalp. Based on signal frequencies that vary from 0.1 Hz to more than 100 Hz, these signals are typically divided into the following categories: delta, theta, alpha, beta, and gamma. The characteristics of the EEG filtered signal have then been extracted using the limited output as an input to the DWT method. The EEG data cannot be filtered in signal processing using a Band Pass filter for diagnostic analysis. Thus, using a high-pass filter at 0.05 Hz and a low-pass filter at 150 Hz is advised for evaluation reasons.

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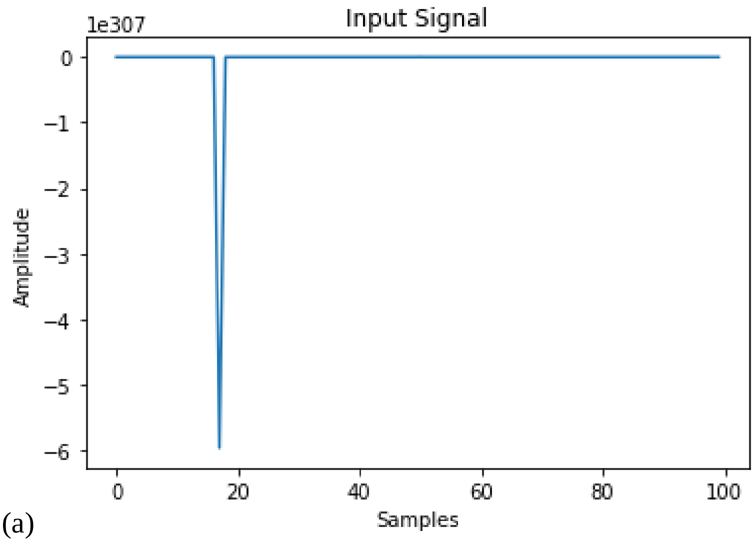
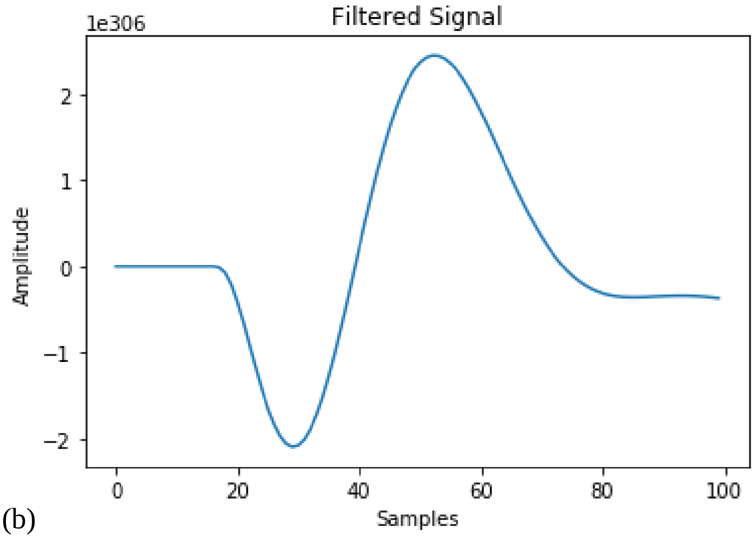
Below Figure 2 shows the input and pre-processing signal for physio net dataset. A material or electromagnetic quantity applied to a device or system in order to create an output action or outcome is known as an input signal.



(a)



(b)

Figure 2. EEG signal for (a) input signal and (b) pre-processing signal

Accuracy

By splitting the quantity of exact forecasts by the overall number of estimates, one can determine the accuracy, which is defined as the proportion of accurate predictions for the test data in Eq.7.

$$accuracy = \frac{f_{correct}}{f_{total}} * 100 \quad (7)$$

In k iterations, $f_{correct}$ represents the number of features that are correctly classified, while f_{total} represents all the characteristics that need to be categorised. Below table 2 shows the compared with existing method accuracy values.

Table 2. Comparison table for accuracy

Machine learning methods	**Accuracy**
QDA	97.5%
SVM	95.0%
KNN	95.0%

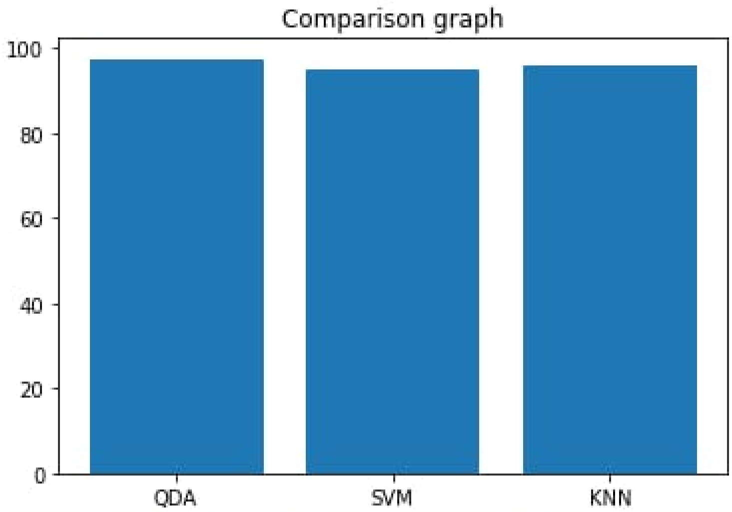


Figure 3. Comparison graph for accuracy.

The above Figure 3 shows the comparison graph for accuracy in proposed method. The propose method QDA accuracy reaches 99.99 which is a higher accuracy value. The SVM accuracy value is 98.6 and KNN accuracy value is 99.75.

Specificity

In simple terms, specificity refers to the true negative rate of an algorithm or model, which represents its ability to accurately predict negative results for all available categories in Eq.8.

$$Specificity = \frac{TN}{TN+FP} \tag{8}$$

Table 3. Comparison table for Specificity

Machine learning methods	Specificity
QDA	96.67%
SVM	93.33%
KNN	95.0%

Above table 3 shows the compared with existing method specificity values. The below Fig. 4 shows the comparison graph for specificity in proposed method. The propose method QDA specificity reaches 99.96 which is a higher specificity value. The SVM specificity value is 96.85 and KNN specificity value is 98.76.

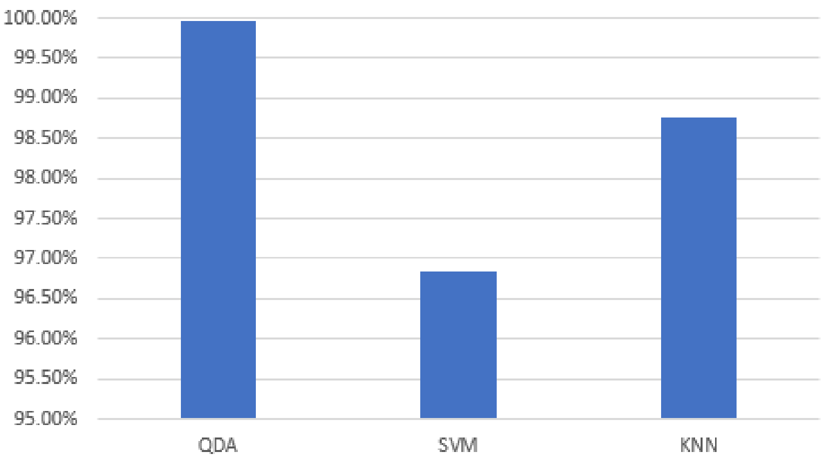


Figure 4. Comparison graph for specificity.

Sensitivity

The ability of a machine learning model to accurately identify positive instances is measured by sensitivity, which is known as e true positive rate. When combined with false negative rate, the total equals 1. A higher true positive rate indicates that the model can effectively identify positive cases with greater accuracy. Below table 4 shows the compared with existing method sensitivity values.

Table 4. Comparison table for Sensitivity

Machine learning methods	Sensitivity
QDA	100%
SVM	100%
KNN	100%

The below Figure 5 shows the comparison graph for sensitivity in proposed method. The propose method QDA sensitivity reaches 99.81 which is a higher sensitivity value. The SVM sensitivity value is 97.34 and KNN sensitivity value is 98.23.

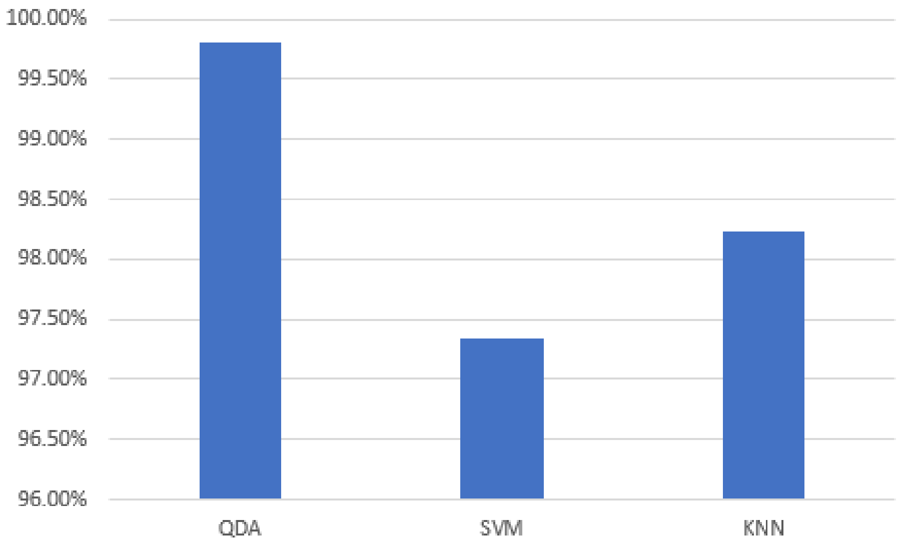


Figure 5. Comparison graph for sensitivity.

Four classification problems have been studied based on the number of EEG dataset groups, which are described below:

1. Control vs mild Alzheimer disorders (two classes)
2. Control vs moderate Alzheimer disorders (two classes)
3. Mild Alzheimer disorders vs moderate Alzheimer disorders (two classes)
4. Control vs moderate and mild Alzheimer disorders (two classes)
5. Control vs mild Alzheimer disorders vs moderate Alzheimer disorders (three class)

Below, the section presents the classification outcomes for the five classification problems.

Control vs mild Alzheimer disorders (two class)

This part addresses first categorization issue (Control vs. mild AD), in which the 35 Rule individuals and the 31 mild AD patients' EEG characteristics were combined to create the "Control" and "mild AD" groups, respectively.

Control vs moderate Alzheimer disorders (two class)

Second classification problem (Control vs moderate Alzheimer disorders) is addressed in section, where EEG features of 20 moderate AD patients have been combined with group of 35 Control subjects to form 'moderate AD' and 'Control' classes, respectively.

Mild Alzheimer disorders vs moderate Alzheimer disorders (two class)

This segment pertains to third classification problem (Mild Alzheimer disorders vs moderate Alzheimer disorders), where EEG features of AD patients (20 moderate) have been combined with group of 31 mild AD patients to form ‘moderate AD’ and ‘mild AD’ classes, respectively.

Control vs mild and moderate Alzheimer disorders (two class)

The following section pertains to a classification problem where EEG features extracted from 35 Control subjects and 31 patients with mild AD have been combined to form the “Control” and “mild & moderate AD” classes, respectively. The aim of classification problem is distinguished between these two classes.

Control vs mild Alzheimer disorders vs moderate Alzheimer disorders (three class)

Fifth categorization issue, that has three classes “Control,” “moderate AD” and “mild AD”, —is covered in part that follows. 35 Control subjects’ EEG characteristics were combined with those from mild AD 31patients to create the “mild AD” class, and twenty intermediate AD patients’ features created “moderate AD” class. To correctly differentiate between these three groups for the diagnosis of AD is the goal of this classification issue. Categorization findings are contrasted in Table 5.

Table 5. A analysis of AD diagnostic categorization rates.

Author	**Pre-processing**	**Classification**	**Extract the Feature**	**Problem**	**Accuracy (%)**
Francesco Carlo Morabito,2016	Notch filter	CNN	-	CS vs AD CS vs AD vs MCI MCI vs ADI CS vs MCI	85 82 75 85
Giulia Fiscon,2018	-	J48	FT, Wavelet	MCI vs AD AD vs CS CS vs MCI AND AD CS vs MCI	80.2 72.2 74.7 71.7
Cosimo Ieracitano, 2020	Notch filter	SVM, MLR, LR	CWT and Bis	CS vs AD CS vs AD vs MCI CS vs MCI MCI vs AD	96.95 89.22 96.24 90.24
Triggiani,2017	band pass filter	ANN	eLORETA	CS vs MCI	76.7
R. Cassani, F. J. Fraga,2017	-	SVM	Amplitude modulation and Spectral coherence	CS vs (severe AD and moderate Brazilian, mild)	84.7
L. Trambaiolli, N. Spolaor,2017	-	SVM	visibility graph, wavelet	CS vs (moderate AD and mild)	76.88%
V. Bevilacqua, A. A. Salatino,2015	-	MLP-ANN, SVM	SVMRFE, PCA	CS Vs AD	86%
J. P. Amezquita-Sanchez, N. Mammone,2019	-	EPNN	fractality dimensions with Music EWT	MCI Vs AD	90.3%
F. J. Fraga, T. H. Falk,2013	Low pass digital filter	SVM	modulation energy Percentage	CS Vs mild, mild Vs moderate, CS Vs (mild +moderate)	98.4% 94% 98.4%
Proposed method	Band pass digital filter	QDA, SVM, KNN	DWT, LBP, RMS, Standard deviation	CS Vs mild, Mild Vs moderate, Moderate vs CS, CS Vs mild Vs moderate, Cs vs (mild + moderate)	99.98% 99.98% 98.5% 99.98% 98.1%

The human brain has the most intricate part from the human body, and it is also an enormous repository of knowledge regarding neural diseases. Additionally, physicians or skilled clinicians identify the preponderance of neurological brain diseases directly by examining EEG patterns. As a result, created a computer-aided diagnostic system in this study that can autonomously analyse EEG data for Alzheimer’s disease and provide an early diagnosis for AD.

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CONCLUSION

This research's main objective is to use EEG data analysis to develop a computer-assisted diagnosis method for AD. The goal was to automate the study of brain impulses in order to increase the speed and precision of the diagnostic process. In order to accomplish this, the EEG data was band-pass filtered and then split into frequency ranges using the DWT method. To improve diagnostic performance, additional signal characteristics including LBP, standard deviation, and RMS were combined with the DWT method. The EEG features were then divided into the appropriate groups using ML methods. The objective of these studies was to compare and assess the most efficient combination technique for correctly diagnosing AD. These studies aimed to compare and assess the performance of different ML methods to find the most effective combination approach for accurately detecting AD. It would like to combine the two distinct machine learning techniques in the future. The suggested grouping and categorization methods may in the future be extended or modified to achieve even greater efficiency. Other combos and clustering methods could have utilized in addition to the tested blend of data mining techniques to increase the detection accuracy. When comparing the accuracy values, it can be observed that QDA has a higher accuracy of 97.5% compared to KNN's accuracy of 95%.

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