Review of Brain Imaging Techniques, Feature Extraction and Classification Algorithms to Identify Alzheimer's Disease

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***Abstract*—Alzheimer's disease is one of the most increasing neurodegenerative disorder which mainly affects the memory, brain functioning and thinking of elders. Since the cure for this disease is yet to be found, it's vital to diagnose Alzheimer's disease in the early stages and to delay the progress of the disease as much as possible. There have been many researches conducted to diagnose Alzheimer's disease using different brain imaging techniques and computational methods. The main aim of this paper is to review brain imaging techniques, preprocessing algorithms and classification algorithms to identify the most suitable approach to diagnose Alzheimer's disease. Specifically this paper consists of following sections: (i) A brief description of the disease and the case; (ii) Review of brain imaging techniques (EEG, MEG, MRI and FMRI); (iii) Review and comparison of preprocessing algorithms (FFT, Wavelet transform and TFD); (iv) Review and comparison of classification algorithms (SVM, decision tree, neural network and random forest).**

***Index Terms*—AD, EEG, FMRI, MRI, MEG, FFT, wavelet transform, SVM, decision tree, random forest, neural network**

I. Introduction

Dementia is one of the most increasing disease and the main cause of death in Australia [1]. The disease mostly starts affecting elders over 65 years. As dementia progresses, the brain starts losing the ability of functioning and thinking rapidly. It has been found that dementia is the first cause of death in women and the third cause of death in men in England based on the survey carried out in 2013 [2]. A detailed information of the survey can be found at [3]. The most common type of dementia is Alzheimer's Disease (AD) which affects 60-80% of people and the second common type of dementia is vascular dementia which is caused by stroke [4]. The main reason of Alzheimer's disease is the damage caused by brain cells [5]. A person's brain is the main part of the whole body and it's the source for every functionality of the body. Thus, when the cells in the brain starts to damage, the basic functionalities of a person's body starts dysfunctioning. The brain contains infinity cells and neurons. Each cell or neuron is connected with each other as "branches" and these branches carry out signals that consists the process of thinking, feelings, memories and etc.

Neurons are connected to each other via "synapses" where the neuro transmitters are travelled. Alzheimer's disease interrupts this process by destructing the brain cells and synapses. Thus, the neurons fail to pass signals which damages the ability to pass the thinking and other functionalities of brain. This disease mainly forms because of two increasing proteins in the brain such as beta amyloid which aids to develop amyloid plaques and Tau which develops tangles in brain cell. There have been many researches carried out based on various brain imaging techniques and it has been aided in detecting and analyzing the progress of Alzheimer's disease in different methods. These techniques can be divided into two types, such as hemodynamic imaging: Functional Magnetic Resonance Imaging (FMRI), Functional Near-Infrared Spectroscopy (FNIRS), and neurophysiological imaging: Magnetoencephalography(MEG) neuroimaging technique and electroencephalogram (EEG) [6], [7].

II. Brain Imaging Techniques

M. A. Oghabian *et al.*, [8], provided a research in where FMRI was used on 40 gender and age matched subjects, 15 elderly, 11 MCI and 14 Alzheimer's patients which showed a vivid pattern activation in brain that differentiates AD and normal patients. Also FMRI detects brain structure using the contrast Blood Oxygenation Level-Dependent (BOLD) to examine the blood flow and oxygen inside the brain which aids to identify the hippocampus regions of the brain. This can be useful in AD since E. E. Tripoliti, [8], has stated that AD patients lack neural activations in parietal and hippocampus regions of the brain.

FNIRS is another hemodynamic approach in where the near infrared light is passed through the brain tissues in order to analyze the state of oxygen throughout the brain and to measure the neuro activation of the brain. Julia *et al.*, [9], proposes a research in where 13 normal and AD patients were examined using FNIRS and they obtained the results of higher parietal activation in healthy subject comparing to AD. Even though hemodynamic imaging provides a valid result, one of the main drawback of this technique is the limited spatial and temporal resolution.

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This can provide a negative impact on the result since Alzheimer's disease brain signals needs a high temporal resolution to identify the functional changes in advance [10].

Thus, it's essential to have a neuroimaging that [10] 1) measures neuronal functions directly, 2) has a high spatial and temporal resolution and 3) has the ability to evaluate functional networks and processes rapidly. These characteristics can be obtained by using neurophysiological imaging since it consists of more spatial and temporal resolution in sub milliseconds which is essential as the neurons activities are carried out in millisecond scale.

MEG being one of the neurophysiological imaging technique, provides the advantage of analyzing magnetic fields of neurons in depth. E. Zamrini *et al.*, [10], conducted a research using MEG on 15 AD and normal patients which provided more accurate results than hemodynamic imaging techniques. It showed that there was an increase in the number of dipoles in the delta and theta band, and a decrease in brain electrical activity in the temporal and parietal regions of both hemispheres of AD patients. Having the most advantage comparatively, MEG can sometimes lead to fatigue and could be complex as it has to be done in a silent magnetic shielded room using Superconducting Quantum Interference Device (SQUID) which indicates that it's not flexible and not easy to use. These minorities can be solved by using EEG, which is one of the most non-invasive and flexible brain imaging technique. It adheres to the requirements of high spatial and temporal resolutions and also has the additional features of mobility and inexpensiveness [11], [12].

EEG has been used in many researches of detecting AD and it has been stated that AD has three main impacts on EEG such as [11]-[13],

Slowing of EEG – Shows an increase in Delta and Theta frequency bands (0.5 – 8Hz) and a decrease in alpha and beta (8-30Hz).

Reduced complexity of EEG – The EEG signal of AD subjects seems to be smoother and regular comparing to similar age matched control subjects.

Perturbations in EEG synchrony – Decreased EEG synchrony in AD subjects who were experimented in resting state.

Slowing of EEG is most commonly concerned in every research in order to obtain accurate results of classifying Alzheimer's disease patients from control subjects or to detect Alzheimer's disease in advance. C. Lehmann *et al.*, [14], proposes a solution based on different classifications in order to analyze the power of classification algorithms in clinical diagnostics. They conducted an experiment using EEG with 45 healthy controls, 116 mild AD patients and 81 moderate patients which produced remarkable results based on the classification approaches assisted with EEG technique. In the recent years most of the research groups [13], [15]-[17] have focused and used EEG to diagnose AD in different ways and have gained desired outputs.

III. PREPROCESSING SIGNAL

Getting brain signals via EEG brain imaging technique can produce many artifacts such as muscular, eye blinks and etc., added to the original signal. These artifacts should be omitted in order to extract the vital signal and analyze it for further clarification.

According to M. Teplan., [18], these artifacts can be divided and described as shown in Fig. 1. The artifacts mentioned in Fig. 1 need to be removed from each signal that has to be analyzed in order to get expected results. Thus, many preprocessing algorithms have been developed and used in previous researches [16], [19], [20].

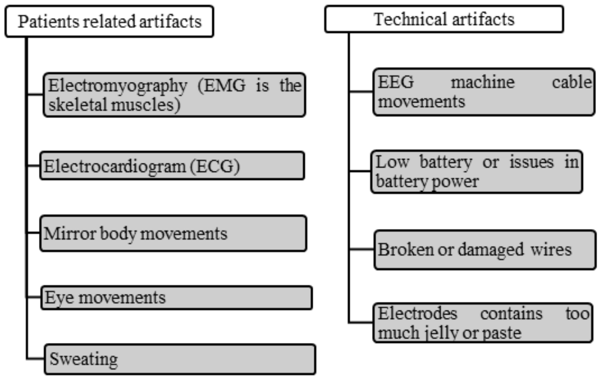

Figure 1. Type of artifacts

A comparison of feature extraction algorithms is shown in Table I. Table I compares four main algorithms used in researches of removing artifacts from EEG. Even though these algorithms have provided accurate results, wavelet algorithm seems more suitable for EEG because it's mainly applied for non-stationary signals since EEG is also one of the non-stationary signal [21], [22].

G. Fiscon *et al.*, [16], used Fast Fourier Transform (FFT) for preprocessing and it was suggested to use wavelet algorithm in order to get a more accurate result. Abdul-Bary Rauf Suleiman *et al.*, [21], stated that FFT provides less accurate results since EEG is a non-stationary signal. One of the main concern using wavelet transform is selecting an appropriate mother wavelet. Selection of mother wavelet reflects the resulting signal. Also another main advantage of wavelet is the selection of windows. The window sizes are adapted depending on the frequency domain of the signal in wavelet transform which means long time windows are used for low frequency resolution and short time windows are used for high frequency resolutions [23].

Wavelet transform is a non-stationary time-scale analysis which measures and analyzes both time and frequency. This algorithm can be chosen to be applied to the EEG signals of both Alzheimer's disease subjects and control subjects which will remove unwanted artifacts and will extract vital signal to classify further. Once the preprocessing is done, the signals taken from Alzheimer's disease and control subjects needs to be trained and classified in order to diagnose the disease. Thus, it's necessary to apply classification algorithms in order to develop these requirements. The next section will include a comparison of classification algorithms.

IV. Classification

Classifying and predicting Alzheimer's disease can be done using different machine learning techniques. This approach has to be done using one or more classification algorithms based on their characteristics. Algorithms can be divided into various types depending on their characteristics. A critical comparison of existing classification algorithms is provided in Table II.

Table II shows the advantages and the disadvantages of different classification algorithms. The results and flexibility of each algorithms depends on the structure of the data and the number of data set. Linear discriminate analysis and logistic regression is suitable if the data is linear whereas Support Vector Machine (SVM) with kernel, Decision tree and random forest can be used for non-linear data.

C. Lehmann *et al.*, [14], proposed a research in where the classification algorithms such as random forest classification, Support Vector Machine and neural were used to classify Alzheimer's disease and control subjects which provided the accuracy of 85%, 89% and 88% respectively. They also have stated that random forest obtains efficient results comparatively and also specifies the important features of the variables which is very informative.

TABLE I. Comparison of Artifacts Removing Algorithms

Algorithm	Advantage	Disadvantage
Fast Fourier Transform	▪ Most suitable for stationary signals ▪ Comparatively faster than other methods available. [24], [25]	▪ Doesn't achieve much accuracy for non-stationary signals such as EEG ▪ Results in frequency domain signal so that the time domain of the signal gets missed [25], [23]
Wavelet transform	▪ Suitable for analyzing transient signals. ▪ Contains both time and frequency information. ▪ Useful to separate and sort non-stationary signal into various frequency parts in different time scale. ▪ Adapts window sizes according to the frequency level. [25], [23]	▪ A proper mother wavelet should be selected. ▪ A proper decomposition level should be selected if it's multilevel decomposition wavelet transform. ▪ Not suitable for stationary signals. [25], [24]
Time frequency distribution	▪ Most accurate results can be obtained by providing clean or denoised signals. ▪ Can be used for non-stationary signals. [25]	▪ The processing stage can be slow because of the gradient ascent computations. ▪ The windowing process has to be completed in the preprocessing phase itself for a proper result. [25]
Autoregressive	▪ Provides best frequency resolutions. ▪ Best suitable for short data segments [25]	▪ Poor spectral estimation if the estimated models are not appropriate ▪ Models should be selected wisely [25]

TABLE II. Comparison of Classification Algorithms

Algorithms	Advantage	Disadvantage
Logistic regression	▪ Good probabilistic interpretation ▪ Possible to update the classifier to obtain new data ▪ Needs less assumption ▪ Suitable for practice classifiers ▪ Performs well even if the variables are not multi-dimensional [26]-[28]	▪ Needs more training set ▪ Makes assumptions regarding the independency of the observation ▪ Data should be structured in a linear method ▪ Not able to identify possible non-linear structures in data [26]-[28]
Linear discriminate analysis	▪ Low computational requirement ▪ Uses hyperplanes to classify classes ▪ Does not change the position of data [29], [30]	▪ Poor results on complex non-linear signals [29], [30]
Support Vector Machines	▪ Most suitable for binary classification tasks. ▪ Useful for insolvency analysis. ▪ Has good generalization properties ▪ Insensitive to overtraining ▪ Update training patterns dynamically [14], [29], [28]	▪ Lack of transparency of results. ▪ High memory requirement ▪ High algorithmic complexity ▪ Speed can be slowed because of the high algorithmic and memory requirements. ▪ Confusion in choosing appropriate kernel method. [14], [28]
Neural Network	▪ Composed of several layers of neurons(Possibly one input, several hidden layers and one output) ▪ Can classify any number of classes which is flexible ▪ Mimics the brain processing intending to solve problems faster	▪ Sensitive to overtraining with noisy and non-stationary data such as EEG ▪ Careful architecture selection and regularization is required ▪ Numbers of layers and input neurons should be carefully selected

	▪ Non-linear technique ▪ Requires less formal statistical training ▪ High tolerance to noisy data ▪ Manages multiple training algorithms [14], [29]	▪ High computational functionalities ▪ Requires long training time ▪ Can be overfitting [14]
Random forest	▪ Expected high accuracy for EEG signals ▪ Provides an estimate of which features are important in the data ▪ Fast and able to handle many features of data ▪ Provides an estimate of generalization error ▪ Provides best result on large data set ▪ Can handle non-linear interactions [14], [31]	▪ Large number of trees makes the performance slow in real time ▪ Needs high amount of labelled data to train and get good results [14], [31]
Decision trees	▪ Not required any domain knowledge ▪ Able to handle high dimensional data ▪ Able to process both numerical and categorical data [32]	▪ Output attribute must be categorical ▪ Output is restricted to one attribute ▪ Known to be unstable ▪ Numeric datasets can be complex [32]

One of the reasons of high accuracy of decision tree might be the feature of handling high dimensional data comparing to other algorithms. Also choosing kernel function for SVM is highly complicated and it might provide less accuracy if the data gets complex.

From the above discussion and comparison of classification algorithms, it's noticeable that Decision Tree and Random Forest provides better results and using other algorithms such as Support Vector Machine, Linear Discriminant Analysis (LDA) and Logistic Regressions needs more planning and proper selection of functionalities and data structures.

G. Fiscon *et al.*, [16], implemented two classifications such as SVM and Decision Trees. It was stated that Support Vector Machine was based on binary classification and implementing multiclass classification required appropriate kernel function and high computational functionalities. Decision tree was also limited by the sensitivity of training data and complexity.

Although these classification algorithms had some limitations [16] they overcame these problems by setting the coefficient of the polynomial kernel function to 2 in SVM and by setting the minimum instances per leaf to 10 in decision tree. However, decision tree provided better accuracy results such as 80% accuracy and 79% specificity whereas SVM provided 58% accuracy and 54% specificity.

Lee *et al.*, [33], also stated that LDA provides higher accuracy in low dimensional feature space and SVM scores higher accuracy in high dimensional feature space. Each classification gains higher accuracy depending on the data given and the field of research. It's believed that classification algorithms such as decision tree, random forest and SVM can gain higher results in the research of Alzheimer's disease with higher collection of dataset.

Shree and Sheshadri [34] proposed a research of classifying Alzheimer's patients and control subjects using Naïve Bays, Random forest, Decision tree and JRIP in where each classification gave the accuracy of 100%, 100%, 98.4% and 100% respectively. The results show that all four classifiers provide good results to predict Alzheimer's disease.

Based on the facts derived from each research, nonlinear classifiers have been showing good results comparing to linear classifiers. It also can be seen that the dataset provided for classification, and the accuracy of data collection provides a huge impact on the final accuracy of the classification.

V. Conclusion

In this paper, Existing work done by various researchers and the impact of Alzheimer's disease in current elders and the damage it causes in brain are vividly explained. Since there is no cure for this disease, the necessity of identifying and controlling this disease has become essential according to many researches as stated in this paper.

One of the main concerns of this research is to identify and select a proper brain imaging technique to analyze brain signal. As the brain signal is non-stationary, it's important to select a brain imaging technique that is high in both spatial and temporal resolution. EEG technique was selected based on the comparisons and discussions that were stated in this paper.

Next a proper and suitable feature extraction algorithm was chosen since the EEG signal may contain lots of unnecessary data. This selection was based on comparing advantages and disadvantages of most used algorithms such as Fast Fourier Transform, Wavelet, Time Frequency Distribution and Autoregressive. Based on the previous researches, wavelet algorithm was selected since it has the ability to analyze both frequency and time.

Finally the classification algorithms were also compared and briefly discussed based on their characterstics.According to the previous researches, it was seen that random forest algorithms and decision tree algorithm provided better results with additional advantages in order to diagnose Alzheimer's disease in advance. In conclusion, Diagnosing Alzheimer's disease can be done by preprocessing the signal using wavelet transform algorithm and classifying it using SVM, decision tree or random forest depending on the facts given in this paper. Naïve Bayes and neural network have also given a good accuracy results. Even though the advantages and the disadvantages of each classifier is stated in this paper, an important fact to be noted is that the data set provided for the research has a huge impact on the final result. Providing a large number of dataset with different features such as gender, age and the level of Alzheimer's disease (MCI, moderate, severe) can result in a higher number of accuracy whereas a small data set may not give much result as expected.

Also as a summary, a proper selection of dataset, preprocessing algorithm and classifier can aid to predict Alzheimer's disease in advance and delay the symptoms of the disease with proper medications.

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