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Machine Learning Analysis of EEG Signals in Alzheimer's Disease Patient: Classification Techniques

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Abstract
Alzheimer's disease (AD) is a neurodegenerative disease that causes problems with behavior, memory and thinking. Commonly dementia or Alzheimer's disease occurred in the person at the age of 60 to 80. Cure from the disease is impossible. Early detection of disease only the solution to the relief of the patient and care taker. AD diagnosis is going through by examining the patients' mental state, neuroimaging scans and laboratory test which takes very expensive and time consuming. Recently electroencephalography (EEG) is used to an alternative technique for the study of AD rather than expensive neuroimaging tools, such as MRI and PET. Machine Learning analysis of EEG provide the diagnosis of Mild Cognitive Impairment (MCI). EEG is the technique used to capture the signal produced by brain with the help of electrodes placed on the scalp surface of head.
This paper aims to the literature survey on various machine learning techniques of EEG signal feature extraction and classification in the signal domain.
Keywords: *electroencephalography (EEG), epilepsy detection, feature extraction and data classification*

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I. INTRODUCTION

Alzheimer's or dementia is a disease with neurodegenerative disorder caused by the damage of neurons in the human brain. Based on the symptom AD can be classified in to three : Pre-Clinical, Mild Cognitive Impairment (MCI) and AD due to dementia.
1.Pre-Clinical stage: In this stage the disease in the brain, in the blood and in the cerebrospinal fluid may start happened in several years ago, but the patient doesn't show any symptom. The possibility of diagnosis AD in the pre-clinical stage provide an oppertunity for therapeutic interventions.[1]
2.Mild Cognitive Impairment (MCI): In this stage the person doing his daily routine independently but feel some memory related issues like difficult to remember the location of usable things, word-finding problem, forget the things that done recently, and decision-making ability or judgment. However it was noted that 30% of cases diagnosed as MCI doesn't leave to AD dementia in recent years.[2]
3.The last stage of the disease is dementia due to AD. In this stage the patients' memory thinking and behavioural symptoms are exposed and effect the ability to function the daily routine in a person.

There are many method for the diagnosis of AD patients such as neuroimaging tools, such as MRI and PET and EEG.

In this paper discuss with The aim of this paper is to recommend the literature survey on various machine learning techniques for the analysis of EEG of AD patients. The sections of this paper are categorized as follows. Section 1 discusses diagnosis of AD patients through EEG and its challenges. Section 2 discuss various machine learning techniques for the analysis of EEG in AD patients. Conclusion of the paper is discussed in section 3 and Section 4 list the references.

1.1 The diagnosis of AD patients through EEG

Recently, the role of machine learning techniques in 'feature extraction' and 'classification of EEG signals' in AD patients has attained a stimulating interest.[3] Here the main focus is on their applications on epileptic seizure detection and translation of brain activities. In healthy persons, EEG signals are often studied by decomposition into several frequencies like alpha, beta, theta, delta waves. Among this, EEG signals in a normal person are often studied by decomposition into several frequencies' delta waves are associated with deep sleep in the frequency range of 0- 4 Hz with high amplitude. Theta waves indicate the time of meditation, idling, or sometimes drowsiness, in the frequency range of 4-8 Hz. Alpha waves have a frequency range of 8-14 Hz which appear when the teste is relaxing or resting. Beta waves reside in the 13- 30 Hz frequency band ranges and they are characteristic of the teste being alert or active, in particular when concentrating. Gamma waves are associated with sensory binding, for example, of sight and sound in the frequency range of 30-100 Hz. However, in the case of Alzheimer disease (AD) patients, each signal is varying from the above frequency bands. For instance, patients with mild cognitive impairment (MCI) shows a change in the frequency range of Beta waves and eventually influence other waves too.

There are many works of EEG Signal to detect early changes in the EEG of people with MCI AD and in cognitively normal people who may be at greater risk for Alzheimer's. Studies specifies that detection of MCI is possible, but more researches are needed before these methods can be used regularly to diagnose Alzheimer's disease in everyday medical practice.

1.2 EEG processing challenges

There are many challenging factors in EEG Processing, the main thing is, it has low Signal-to-noise ratio(SNR) [4], as the activities of brain evaluated under different source of environment physiological and activity-specific noise of homogenous or larger amplitude called "artifacts". Different preprocessing and noise reduction methods have to be used to minimize the noise source and to extract true brain activity from the recorded signal. Various filtering and noise removal methods are to be used to reduce the impact of unwanted signal and to extract true brain signal from the recorded signal.

II. METHODS

2.1 EEG Signal Analysis Methods Used for Mild Cognitive Impairment(MCI) Patients

The Coupling Analysis Methods

DongWen, YanhongZhou and Xiao Lili propose a review on "A Critical review: coupling and synchronization methods work in application to EEG signals of MCI patients"[5]. Several methods were proposed to study the coupling features between two EEG from different area of brain of MCI patients, such as coherence[6],mutual information[7] synchronization likelihood (SL) [8]Granger causality[9], and permutation conditional mutual information (PCMI) [10]

2.2 For the method of coherence, estimates the linear correlation between two time series on frequency domain. Evaluate the MCI patients with depression by using the method, and exhibit the output as the MCI patients with depression were different significands with the Healthy persons in coherence strength between frontal and temporal area. However, the method does not examine the owner non-linear properties of signals.

2.3 For the method of mutual information, it compute the own and joint probability density distribution of two time series, and evaluates the statistical independence between two time series by calculating various entropies. Liu et al[11] examined the change related to the task in neural oscillation and connection between cerebral cortex of MCI patients and Healthy person, and identified that MCI patients were significantly different from Healthy person in the neural oscillation strength and connection between parietal and occipital on theta frequency band. However, the calculation of mutual information needs longer data, and shorter data are not enough to make the result of computation have statistical significance.

2.4 For the method of SL, it is implemented to compute the degree of dynamic interactions between time series multiple time series. Many research works disposed that the SL could be used for examining EEG signals of MCI patients: SL strength between EEG signals from frontal–parietal of MCI was lesser than Healthy person on alpha frequency band, the SL strength between EEG signals from frontal–parietal of MCI was lesser than Healthy person on delta frequency band[12], and the SL strengths of EEG signals of MCI were larger than Healthy person on low alpha frequency band (8–10 Hz) [13]. On the method of SL, the likelihood extent of time series patterns is computed with statistical method, and this method ascertains which time series pattern is homogeneous with other time series patterns according to threshold. The similarity is not considered in the decision-making process[14], and it will influence the accuracy of the method on diagnosing MCI to some extent.

2.5 The Granger causality measure the degree of linear inter dependence between different signals, and was often used in examining the linear model of EEG signals. The linear methods of Granger causality include partial directed coherence (PDC) and Directed Transfer Function(DTF), they belong to parametric method with multivariate auto-regressive model[15], and may explain the causality between multi-dimensional EEG signals on particular frequency band. The Granger causality methods gained some valid output preliminarily in examining the EEG signals of MCI: the all frequency DTF of MCI decreased significantly in comparison with Healthy person[16], the direction index of information flow from parietal to frontal part of brain of MCI and AD decreased relative to Healthy person, and especially the lesser became significant on alpha and beta frequency bands[17]. The selection of order of multivariate auto-regressive model is difficult during calculating the parameters of multivariate auto-regressive model. Because lesser order affects the correctness in calculating model parameters, greater order can improve the accuracy and needed longer EEG signals to involve the computation.

2.6 PCMI is a non-linear method, is used to calculate the coupling strength and direction of two time series from neural mass model, and to compute the coupling strength and direction of time series of epilepsy and spike potential series.[18]

The following Figure 1[19] illustrated how the coupling and synchronization methods work in application to EEG signals of MCI patients

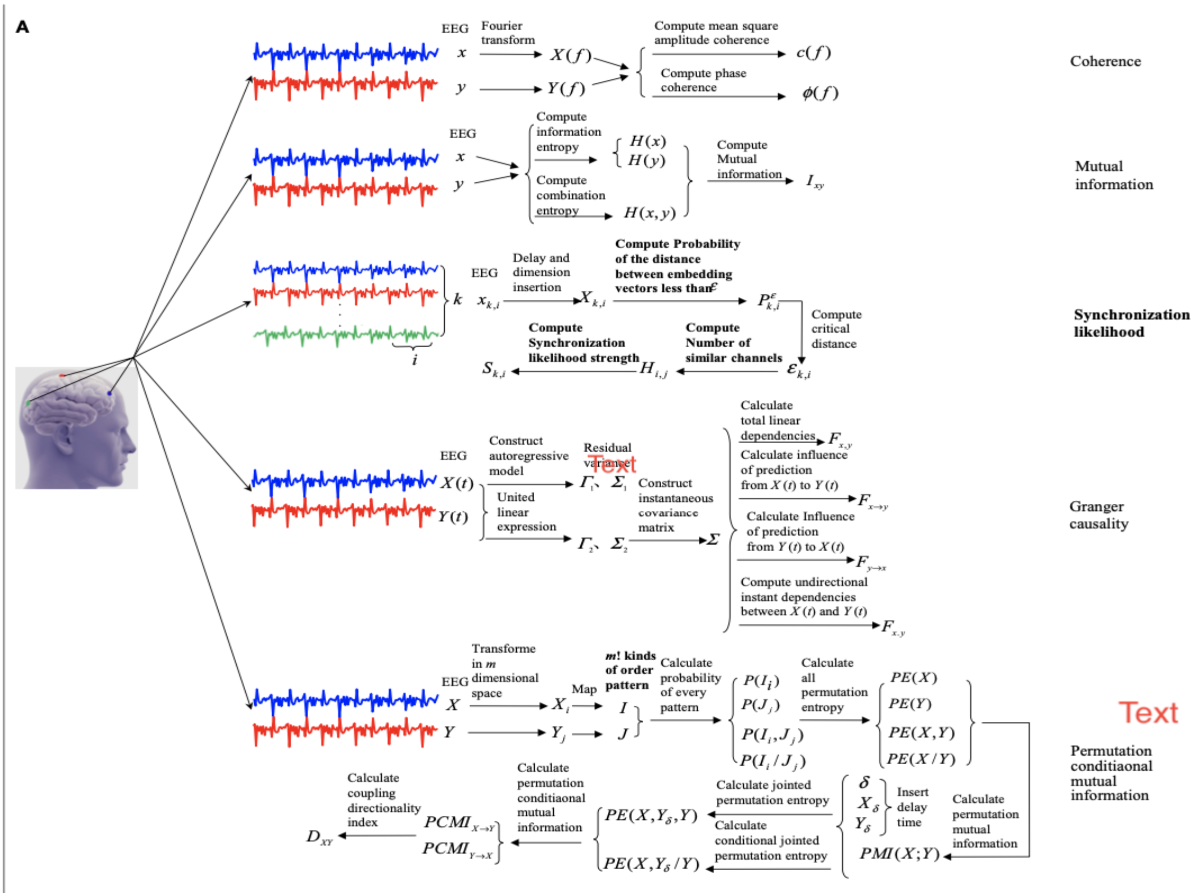

FIGURE 1 | The working pattern of five coupling and six synchronization methods with application to EEG signals of MCI patients. (A) showed working pattern of five coupling methods, and *(continued)*

2.7 In Seizure detection with spectral power EEG using cost-sensitive Support Vector Machine method, Yun Park, Lan Luo, Keshab K. Parhi, and yTheoden Netoff proposed[20] that consists of pre-processing, feature extraction, SVM classification, and postprocessing. Pre-processing eliminates artefacts of intracranial EEG recordings and they are further pre-processed in bipolar and/or time-differential methods. Features of spectral power of raw, or bipolar and/or time differential intracranial EEG (EEG) recordings in nine bands are removed from a sliding and half overlapped window. Nine bands are selected based on standard EEG frequency bands, but the wide gamma bands are converted into four. For classification it was used Cost-sensitive SVM for preictal and interictal samples, and apply validation process to achieve in-sample optimization and out-of-sample testing, also postprocess using Kalman Filter in SVM classification, it removes sporadic and isolated false alarms. From 18 patients of 20 available, the algorithm has been tested on EEG in the Freiburg EEG database who had three or more seizure events. To investigate the distinguishability of the features between preictal and interictal, use the Kernel Fisher distinguishable.

PROBLEMS AND DIRECTIONS.

Recently many number of machine learning methods have been established, here the author propose a method for feature extraction and classification of EEG Signal for Pre-Clinical and MCI of AD. The method which the author is going to propose give more accuracy compared to the above mentioned machine learning methods. Many researches have done the diagnosis of AD using MRI image as the input dataset. The problem in MRI image recognition is that, it is very difficult to diagnosis Pre-Clinical and MCI of AD and expensive.

There is a requirement for continuous evaluation of patient through their symptoms to diagnosis early. So analysis of EEG is better than MRI. The current scenario wasn't much explored in the deep learning analysis of EEG of the particular disease. The methods like CNN deep learning gives more accuracy over SVM [21].

CNN Deep Learning

We propose a CNN based deep learning method because the method is able to uproot spectral, spatial and temporal features from EEG data and use them to analyse common structure of a seizure that is not much sensitive to variations, as EEG signal show considerable sensitivity on noise and have low signal-to-noise ratio. Apart from that problem can be caused by artifacts in EEG recording and feature extraction.

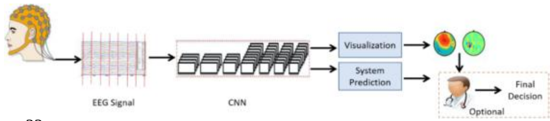

Figure 2[22] (Block diagram of the proposed seizure detection)

III. CONCLUSION

AD is a is a neurodegenerative disease that affects millions of people in the world, and increasing this number will continue in all prospects. There is no complete recovery from the disease if it was not diagnosed in early stages, till today. It is of even much more concern the lack of solidness and the tardiness in the diagnosis. Two main problems have been stippled on one hand, patients, friends and their family members do not realize about AD symptoms until being too late, so when they attend specialists the treatments for delaying the symptoms are not already effective. On the other hand, specialists have real difficulties for diagnosing AD, because not all physiological changes can be easily detected and furthermore, most of the biomarkers are not unique to AD. A solution capable of handling with these problems is needed in order to achieve early AD diagnosis that could give better life quality of the patients and his companions or care takers, diminishing the effects of the disease and increasing their life expectations.

Due to the fact that most of AD symptoms are not unique compared to other neurological diseases, it is necessary to find a unique method for early stage diagnosis through continuous evaluation of patient via EEG. Deep learning analysis method could allow to make a reliable diagnosis of all kinds of symptoms, detect even the smallest changes and combine them, so as to detect MCI AD as early as possible.

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