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ELECTROENCEPHALOGRAM BASED DEPRESSION ASSESSMENT USING MACHINE AND DEEP LEARNING TECHNIQUES: A SURVEY

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Abstract: Depression is a serious malady. It has shown to affect people of all age groups and is a growing cause of suicides. The electrical activity of the brain is depicted through electroencephalogram (EEG) signals. Studies have shown that EEG signals are a major indication of a person's emotional state and hence are used in a huge number of studies on depression assessment. Deep learning is gaining ground in depression assessment using EEG signals. This paper summarizes the various methods used to assess depression using EEG signals, through machine and deep learning techniques.

***Index Terms* - Electroencephalogram, deep learning, emotion recognition, depression.**

I. INTRODUCTION

Depression is characterized by a sense of insufficiency, discouragement, decreased activity, negativity and sadness, which greatly impact the person's life [1]. This has prompted researchers to work extensively on it. Even young kids nowadays are affected by it, and hence diagnosing it at the right time has become utmost important. Depression can be manifested in many forms. Electroencephalogram (EEG), electrocardiogram (ECG) signals, visual, vocal cues and some others are popularly used to detect depression in a person. Earlier, we observed that machine learning algorithms were used for processing of biomedical signals [2][3][4][5][6], but now deep learning can be seen becoming the trend. The earlier papers coded the hand-crafted feature extraction part and classification part separately to achieve the required goal. With deep learning, this whole process is automated and made into a single structure which takes raw EEG signals and gives the desired classified output. A systematic survey of the major studies done on depression assessment using EEG through machine and deep learning techniques, has been attempted in this paper.

The rest of the paper is structured in the following way. Section 2 has the literature review of previous studies. Section 3 talks about EEG signals with respect to depression in detail. Section 4 gives information on the datasets used in previous studies for EEG based depression assessment. Section 5, 6, 7 discusses and analyses the different stages of depression assessment. Section 8 elaborates on the results obtained by the different studies considered and section 9 talks about open discussions, challenges and future directions for the study.

II. LITERATURE REVIEW

Researchers have used several methods to assess depression. Continuous research by them has helped make significant progress in it over the time. M. Ahmadlou [7] in 2012 used an Enhanced Probabilistic Neural Network with two hidden layers to assess major depressive disorder (MDD). Puthankattil SD [2] in the same year used a two hidden layer Artificial Neural Network (ANN). O. Faust [3] in 2014 tried using seven different classifiers to achieve the goal. They were Support Vector Machine (SVM), Finite State Classifier (FSC), Probabilistic Neural Network (PNN), Naive Bayes classifier (NBC), k-nearest neighbors (k-NN), Gaussian mixture models (GMM), and Decision Tree (DT). Out of them, PNN outperformed every other classifier. In 2015, U. R. Acharya [4] used SVM, k-NN, NBC, PNN, and DT for classification, out of which, SVM gave the best results. Likewise, in 2017, W. Mumtaz [5] used logistic regression (LR), SVM and NBC for classification and SVM's performance stood out. S.-C. Liao [6] used k-NN, Linear Discriminant Analysis (LDA) and SVM, and SVM again proved to be better than the others. But all these studies had to preprocess and extract important features manually to achieve the goal. With the rise of powerful deep learning algorithms, cheaper computational power and other advancements facilitating the use of such algorithms, it was observed that end-to-end methods [8] could be built to do the work. In 2018, Acharya, U. [9] just used Z-score normalization and the rest of the work was done by a 13-layer CNN model. In 2019, Ay, B. [8] made a Convolutional Neural Network - Long Short Term Memory hybrid deep learning model to solve the task. It could learn both the local features and the long-term dependencies from input signals, resulting in great accuracy. In 2020, X. Li [10] was able to recognize mild depression in a person, which benefits greatly since people can then take adequate measures to mitigate it, before it becomes severe and irreversible. A combination of functional connectivity matrices and 4-layer CNN was used in the study for classification of mildly depressed and healthy subjects.

III. EEG for Depression Detection

The EEG signals are spontaneous biopotential signals which are recorded from the scalp. EEG, being a non-invasive technique, is widely used to analyse various brain disorders [11]. Studies have also shown that EEG signals have significant changes when the person under study is depressed. A study has also shown that the right hemisphere of the brain becomes more active during depression as compared to the left one [9]. This is because, during depression, the right hemisphere's frontal cortex's activation is higher than that of left hemisphere [12]. EEG signals are classified into - Alpha, Beta, Theta and Delta, based on their frequency. Beta waves demonstrate most of the electrical activity in an anxious or exhilarated person [13]. Signals can be of two types – resting state and stimuli based EEG signals. Fig. 1 below shows a general workflow of EEG based depression assessment.

IV. Datasets

Different studies listed in Table 1 below have used different datasets for the task. Except [7], all the other studies under consideration have used resting state EEG signals. X. Li [7] used a visual stimulus while recording the EEG signals of the person. Some of these datasets were obtained from a different source, and some were created by the researchers. Clinical diagnosis by psychiatrists was used to confirm depression in a subject. Most of the studies mentioned have chosen a dataset of 30 subjects (15 depressed and 15 healthy) [2][3][4][8][9]. The EEG datasets for each subject contains 19 signals, in accordance with the 10-20 international standard protocol [7]. The studies recorded their subjects' signals for around 1 to 5 minutes. One of the famous (15 + 15) dataset is the one obtained from the Psychiatry Department, Medical College, Calicut, India, which was used by [2][3][4][8][9]. In this dataset, subjects are between 20 to 50 years old. Bipolar EEG signals from the left hemisphere (FP1-T3 channel pairs) and the right hemisphere (FP2-T4 channel pairs) of the brain were considered. Each subject was recorded with their eyes open and then closed for 5 minutes. Notch filtering at 50 Hz was also done on this dataset to remove power line interference.

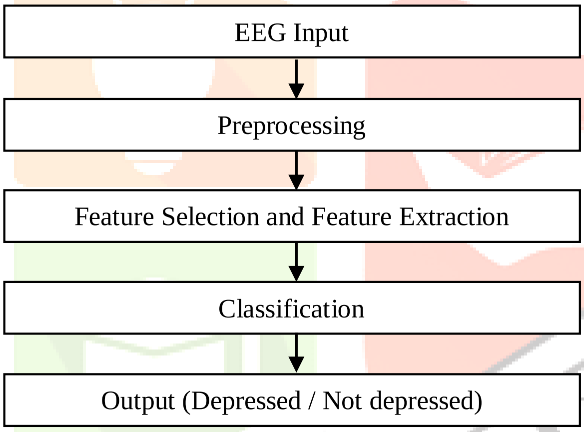

Fig. 1. Block diagram for general workflow of depression assessment

V. Sampling and Preprocessing

Sampling is done on the raw EEG data which converts the continuous time-signals to reduce them into discrete time-signals. Most of the studies [7][2][9][8][3][4][5] that are listed in Table 1 have used a sampling rate of 256 Hz. The preprocessing stage in the workflow drawn in Fig. 1 helps to remove noise from the signals which may be added from blinking of the eyes and muscle activity. These noises can distort the signals and hence, need to be removed. Mainly electrooculogram removal, event extraction, EEG subsection and pseudotrace removal are carried out in the preprocessing stage [13]. Table 1 enlists the approaches followed by studies for preprocessing the data.

VI. Feature Selection and Feature Extraction

The next step in the workflow is finding out the important features of the EEG which will help achieve our purpose. This is important since working on only the necessary features will lead us to better and faster results and that too through lesser computation. Studies were seen to differ in the selection of features and the methods they used to extract them from the preprocessed EEG. The feature extraction methods used by the papers that are taken into consideration are mentioned in Table 1. But some approaches for the study do not require the feature selection, extraction, and reduction stages [9], like in [8][9][10].

VII. Classification

The final step in detecting depression is to binary classify the extracted important features of EEG signals into "depressed" and "healthy" classes. Machine learning/deep learning models are applied to achieve this step. Support Vector Machines were used in [4][5][6]. It works very well with high dimensional data and considered as a high efficiency classifier model [5]. Its hyperplane is able to separate depressed and healthy patients with a very good accuracy, as it can be seen in [4][5]. Neural networks still have been the top choice for many researchers as a classifier for depression assessment as seen in Table 1. They comprise of an input layer, one or multiple hidden layers and an output layer. They have the ability to learn very complex information and give amazing results. Convolutional

Neural Network (CNN) is one of the frequently used neural networks. It has three kinds of layers which in order are - convolution, pooling, and fully - connected [9]. Useful features and information can be extracted efficiently from the EEG signals using this neural network [8]. But since EEG is a time-series data and CNNs do not have memory, a recent study [8] made a hybrid model of Convolutional Neural Network and Long Short Term Memory networks so that the combined model also has both short and long term memory of previously occurred data. The table below gives a brief overview of the earlier prominent studies done on this topic.

Table 1. Previous studies on EEG based depression assessment

References	**Sample (Depressed + Healthy)**	**Preprocessing**	**Methods of feature extraction**	**Classifier**	**Accuracy obtained (In %)**
M. Ahmadlou (2012) [7]	15 + 15	Wavelet and spectral bands (Fourier), Bootstrap	Fractal dimensions and wavelet filter bank	Enhanced Probabilistic Neural Network	91.30
Puthankattil SD (2012) [2]	15 + 15	Wavelet, total variation filtering, multiresolution decomposition	Relative wavelet energy	Artificial Neural Network	98.11
O. Faust (2014) [3]	15 + 15	Wavelet package decomposition	Nonlinear features and wavelet packet	Probabilistic Neural Network	98.20 (Left hemisphere) 99.50 (Right hemisphere)
U. R. Acharya (2015) [4]	15 + 15	Broadband	Nonlinear features	Support Vector Machine	98.00
W. Mumtaz (2017) [5]	33 + 30	Fourier	Power of frequency bands and alpha interhemispheric asymmetry	Support Vector Machine	98.40
S.-C. Liao (2017) [6]	12 + 12	Linear regression, Electroencephalogram-Vertical-Electrooculographic (EEG-VEOG) covariance analysis	Kernel Eigen-filter-bank common spatial pattern	Support Vector Machine	81.23

Table 1. Previous studies on EEG based depression assessment

References	**Sample (Depressed + Healthy)**	**Preprocessing**	**Methods of feature extraction**	**Classifier**	**Accuracy obtained (In %)**
Acharya, U. (2018) [9]	15 + 15	Z-score normalization	-	Convolutional Neural Network	93.54 (Left hemisphere) 95.96 (Right hemisphere)
Ay, B. (2019) [8]	15 + 15	-	-	Convolutional Neural Network - Long Short Term Memory hybrid model	97.66 (Left hemisphere) 99.12 (Right hemisphere)
X. Li (2020) [10]	24 + 27	Net Station Waveform Tools, Fast algorithm for Independent Component Analysis (FastICA)	-	Convolutional Neural Network	80.74

VIII. RESULTS

Researchers have been able to achieve between 80% to 100% classification accuracy in their studies. SVMs gave an accuracy of 98.00% [4], 98.40% [5] and 81.23% [6]. The variety of neural networks used in different studies also gave good results. The Enhanced Probabilistic Neural Network used in [7] achieved an accuracy of 91.30%. The ANN in [2] and PNN in [3] achieved an accuracy of 98.11% and of average 98.85% respectively. The deep CNN in [9] resulted in 94.75% accuracy on an average. Ay, B. [8] was able to achieve an accuracy of 97.66% and 99.12% for the left and right hemispheres of the brain respectively. The 4-layer CNN in [10] could classify 80.74% data accurately. Different studies used different metrics to analyse their results. M. Ahmadlou [7] used one-way Analysis of variance (ANOVA) test to analyse their results. Multiple studies [3][5][8][9][10] used some sort of k-fold cross validation technique. Leave-one-out and k-fold cross validation seemed to be the popular choice among researchers to evaluate their models in such a type of study [14].

IX. OPEN DISCUSSIONS, CHALLENGES AND FUTURE DIRECTIONS

The aim of this study is to help researchers easily understand various methods that had been used till now for assessing depression using EEG signals. The basic and important steps of assessment used by the studies under consideration have been discussed. There are certain areas that have a scope of improvement. A lack of external validation is seen in many studies [14]. Such validation is important for improving the reliability of the developed models. Bigger datasets need to be developed to achieve this, since studies till now had been working on the EEG of only a few subjects. Also, on using a bigger dataset, the models can be trained more and made more robust. The models will also become more robust and reliable when the dataset will contain diversity in terms of race and other parameters. Wireless EEG caps have also come into the market, which will help a lot since until now we were restricted to settling in a place to record our EEG signals, which would not be required now. Also, Functional Magnetic Resonance Imaging (fMRIs) and Magnetoencephalography (MEG), along with EEG can be used to detect depression for more reliable results. With internet becoming cheap and easily available, web and mobile applications can also be made which will do all the required work once given the input signals, so that our depression assessment is just a click away. Furthermore, if we have a dataset that has monitored EEG signals of some specific people over a span of years, we can use it to predict if those people will have depression in the future or not. This area is not much explored and accurate, reliable results in this can save many lives.

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