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Diagnosing Mental Disorders based on EEG Signal using Deep Convolutional Neural Network

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Abstract

Suicides are on the rise all across the world, and depression is a prevalent cause. As a result, effective diagnosis and therapy are required to lessen the symptoms of depression and anxiety. An electroencephalogram (EEG) is a device that measures and records electrical activity from the brain. It can be used to generate a precise assessment on the severity of depression and anxiety. Previous research has shown that EEG data and deep learning (DL) models can be used to diagnose various psychiatric disorders. As a result, this paper offers DeepNet, a DL-based convolutional neural network (CNN) for identifying EEG data from depressed, anxiety and healthy people. This study examines DeepNet's performance in two trials, namely the subject wise split and the record wise split. DeepNet's results have an accuracy of 0.9837, and when record wise split data is used, the area under the receiver operating characteristic curve (AUC) is 0.989.

Keywords:CNN, Deep Learning, EEG, record wise, subject wise

1. Introduction:

Deep learning has a long and rich history, but it has won many names that reflect different philosophical views, and its popularity has fluctuated. Deep learning enables you to solve increasingly complex applications with greater accuracy. The current generation of machine learning models also discusses more general principles of combinatorial hierarchical learning, which can be applied to machine learning frameworks that are not necessarily based on the nervous system. Simple linear model based on neuroscience. Misery positions fourth among the main ten infections on the planet [1]. As per insights from the World Health Organization (WHO), in excess of 340 million individuals overall experience the ill effects of melancholy of changing degrees. Depression is the main cause of stress worldwide. It is defined as lack of motivation, difficulty in having fun, negative effects on daily activities, and in severe cases, it can lead to suicide. According to Chinese statistics, more than 30 million Chinese people suffer from depression. It is estimated that by 2021, depression will become the second leading cause of death [2].Heart disease in the world. Patients with depression will have serious psychological problems and negative emotions, usually manifested as sadness, tiredness and despair. Patients with severe depression may even exhibit suicidal behavior. Clinical research on depression has been conducted steadily from the mid-nineteenth century. Clinical diagnosis of depression has grown challenging due to the unknown underlying neurological mechanism and pathogenic concept. The International Statistical Classification of Diseases and Related Health Problems, 10th edition produced by WHO and thus the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition developed by the us are now the foremost widely used international diagnostic criteria. the standard interview and questionnaire-based procedure necessitates a serious amount of some time and energy. Sensor networks are widely employed in fields like healthcare and biology in recent years [3]. EEG technology is increasingly being utilised to help within the identification of illnesses like schizophrenia, moderate cognitive impairment, epilepsy, and Alzheimer's. an honest link has been shown between the brain and depression specifically. The cognitive aptitude of depressed individuals fluctuates with their mood, and these variations impact the EEG. As a result, more studies do electroencephalogram (EEG)-based research to investigate objective and widespread diagnostic tools and procedures for depression. Although EEG technology is utilised to assist within the diagnosis of depression, the foremost widely used EEG collection devices for research purposes are 128-electrode and 256-electrode brain caps. Before using the EEG collection equipment, wet the brain cap or apply the conductive paste on the relevant electrode site. Figure 1 shows the position of electrodes placed in the head.

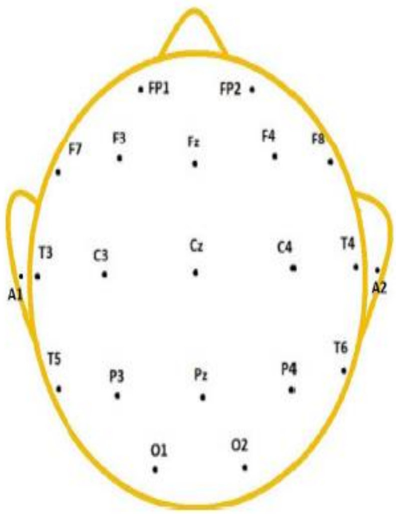

Fig.1.Shows the explanation of Electrode placed in the head.

The experiment's process is quite difficult, and also the pollution is relatively huge. and since the patient feels uncomfortable while wearing this equipment, it's simple for them to travel away during the EEG monitoring, making it difficult to collect an enormous sample size [4]. Social anxiety disorder (AD) is very common and has many comorbidities. In this study, we analyzed the effects of working memory (TM) training on various interventions that may be related to AD, preselected AC symptoms, or active treatment control. (Social) Anxiety and sadness, as well as measures to assess TM, control disorders, attention distortions, and evoked event potentials (ERP) for evaluation before and after treatment. Improved the performance of the SW transmission task, reduced the symptoms of SA, and changed the amplitude. The effect of WM training on AS symptoms. These results are the first evidence that WM training can help reduce the potential incidence of AS, but more research is needed to determine the causal relationship between these rates [5].

2. Literature Survey:

The current research has several limitations: The predictive effect size used in the previous power analysis may be too optimistic, indicating that the sample size is not sufficient to detect significant learning effects in comparisons between groups, especially for the behavioral bias index. Therefore, we cannot be sure whether the performance improvement of the training group reflects the real impact of the training, or is just the "return to the mean" of the measurement. Only the N170 and N2 components have significant changes in amplitude after training compared with the control group [6]. The limitation is one of the main findings, that is, the obvious relationship between AS symptom intensity and MW transmission power is constant in all analysis levels (group or individual). A. Seal, R. Bajpai, J. Agnihotri, A. Yazidi, E. Herrera-Viedma and O. Krejcar in 2021, another limitation of the Dotprobe test is the use of unusually angry faces. Include incentives with broader emotional content. Although the Dotprobe task is unreliable and the ERP signals received during task execution have a limited correlation with (characteristic) anxiety (eg Kappenman et al., 2014), future research should (also) use alternative tasks to avoid attention Force to distort and investigate their connection. How about it. The purpose of this study is to create a unique multi-modal model by combining multiple electroencephalogram (EEG) data sources that receive neutral, negative, and positive hearing stimuli to distinguish depression patients from normal people. 86 depression patients and 92 control patients were simultaneously recorded under the influence of different auditory stimuli. Then extract linear and nonlinear characteristics from the EEG data for each mode and make selections to generate mode-specific characteristics. In addition, a linear combination method is used to combine the EEG features of multiple modalities. In addition, evolutionary algorithms are used to weight features to improve the overall performance of the recognition system. The KNN classifier has the highest classification accuracy, reaching 86.98%. The positive and negative auditory stimuli indicate that the fusion model may provide higher accuracy in defining depression than the single model approach. Depression is a dangerous neurological disease characterized by a marked lack of interest and may lead to suicide. According to the Rajendra Acharya, Reza Khosrowabadi & Vahid Salari(2020), the disease affects more than 300 million people worldwide and is the most common cause of disability. Maps the ongoing research using non-invasive EEG to detect depression biomarkers from 2014 to the end of 2018. Our research reviewed more than 250 articles and discussed the results of 42 studies and promising biomarkers, and found that the depressed brain seems to have a network structure. Random and promising diagnostic features, such as gamma range and signal complexity, can identify specific symptoms of depression, such as suicidal ideation [7]. Lamyaa Sadouk , Taoufiq Gadi, and El Hassan Essoufi(2018), This work has several limitations; for example, the screening process is carried out by one person, which affects the completion and reporting time, so only vacancies were found before November 2018; it also affects internal efficiency, because subjective decisions will affect the review process; In order to alleviate this situation, we limited the comparison to age and made detailed notes with Mendeley (Mendeley, 2019) and Parsifal (Mendeley, 2019). (Parsifal Systematic Review Tool, 2019). In Taban Eslami & Fahad Saeed(2019) paper , our selection criteria exclude articles that only compare treatment response, although they may help to better understand the biomarkers of depression and should be discussed in the future[8]. Learn more at the difference between unipolar depression and bipolar depression is very important in clinical practice. However, several direct studies compared the EEG activity of these groups. We examined the activity of the left and right alpha1, alpha2, and theta frontal lobes on the EEG of 87 participants in response to unipolar (UD, n = 33), bipolar (BD, n = 22), and healthy adults. face. There is also depression. (HC, n = 32). Subsequent analysis of the observed hemisphere x group interaction (p. 037) only revealed a significant change in alpha1 asymmetry when comparing UD and HC (p. 006). x (p = 0.001) shows that there is a difference in the effect of stimulus titer on theta power between (p, 001). The BD value is different from UD (S.0002) and HC (S.004), depending on the effectiveness of theta. Alpha1 asymmetry correctly identified CH and the two depression groups. 69. Theta related to Valentina correctly distinguishes between BD and UD. 83. Using a single pin for cross-validation will result in slightly lower accuracy. Suman Raja, Sarfaraz Masood (2019), in this paper research has some important limitations that may limit its effectiveness. The limited sample size is a major shortcoming of the current research. In addition, we did not observe any patients who were emotionally happy or (hypomanic). Another major limitation is that patients cannot get rid of drugs. In addition, the facial stimuli used in the current study have not been rated by humans, and we did not include stimuli that control the arousal effects of happy and sad facial stimuli. Another limitation is that we cannot use the mastoid electrode as a reference in our setup. Instead, we use a reference media mount, which can be enhanced by a higher density sensor array. Another possible flaw in our research is that we are using task-based design, which reduces repeatability. However, we chose this strategy because of its added value in identifying group differences in emotional stimulus processing [9].

3. Dataset Description

To train network, free source data from ieee data port (depression & anxiety) were downloaded and trained. In deep cnn 50 depression subjects and 150 anxiety subjects have used to diagnosis depressed and anxiety people. This dataset has been collected from 4 to 80 years of age subjects (both male and female). The raw data was gathered at medisys hospitals in Hyderabad, India, using an allegers Virgo EEG machine. The raw data contains the .csv files. In each patient's .mat file, rows indicate to samples and columns indicate to channels.

3.1 PCA- Principal Component Analysis

In the preprocessing method "Principal Component Analysis" (PCA) is used, and it's also utilized in features extraction stage .Without lack of information data, data may be analyzed and dimensions of fact may be decreased the use of this technique. The data at unique time collection multi- channel may be extracted the use of this technique. Principle additives may be produced and sign size may be decreased with the aid of using the artifacts' removal. Mainly sixteen features have been reduced to diagnosis of Depression and Anxiety [10,11].

3.2 CNN- Convolutional Neural network

In this paper Convolutional Neural Network was implemented to diagnosis of Depression and Anxiety. In CNN, In each layer neuron will simplest be linked to a each location of the layer that's to be had not like the conventional completely linked network, wherein a neuron could be linked to the each and every neuron of the layer earlier than it. CNN has Hidden layers, Convolution layer, RELU layers and a Pooling Layer. In this Proposed Architecture one fully linked layer and it includes a convolution layer and more than one hidden layers, ReLU layers, a pooling layer. To extract features, Convolution layer and pooling layer are used and to do classification fully connected layer is used. As expected, CNN adapts to research non-linear facts in view that the real-global facts to be discovered in normally non-linear. Since the convolution layer is linear in operation, the ReLu layer is brought in assisting to transform linear operation to non-linear [12]. In Proposed Architecture 5 convolution layers, five normalization, 5 max pooling layers and 3 fully connected layers has been used. Each and every layer uses the ReLU activation function and whereas the last fully connected layer uses softmax. Figure 2 depicts the layout of these layers.

3.3 Convolution layer:

Convolution is a method for signal transformation procedure that produces altered and relevant signals. A time-variant and linear filter is need for convolution This is applied This is applied to the signal and multiplied and translated to produce new signal values .In cnn, the very first layer is convolution layer which is the input layer. For all layers, the number of filters utilised is either 128 or 64 or 32. The C1, C2, C3 convolutional layers are convolved with a filter size of 1*5. The fourth and fifth convolutional layers have filter sizes of 1*3 and 1*2, respectively. When employing a Neural Network to implement convolution, Every convolution layer a kernel/filter is slid over the input signals to produce an output, which is also known as the layer's activation map. To convert EEG data into a low-dimensional space, we chose 128 filters for C1 to extract the majority of the relevant low-level features and minimise the amount of features as the network depth increases. Only the most crucial high-level relevant features are included in the C5 layer [13].

3.4 Batch Normalization:

By normalising the output of the previous layer, batch normalisation is used to stabilise the network. Convolution includes five batch normalisation layers, one after each convolutional layer.The output of the batch normalisation layers, the network employs the Leaky ReLU activation function. When batch normalisation is used, the convergence rate is higher when compare to batch normalisation is not used [14].

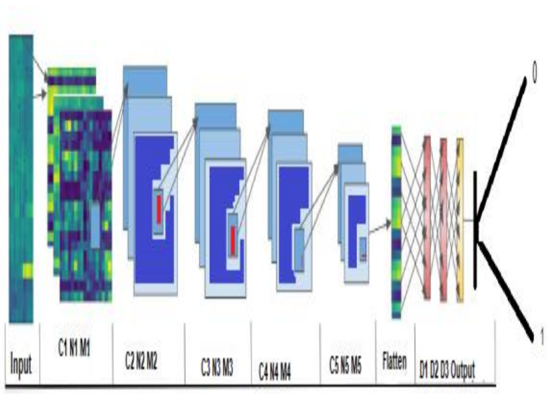

Fig. 2: Architecture of Proposed Algorithm

3.5 Pooling layers:

On the temporal dimension, the network uses 1-D pooling procedures. In pooling layer, the filter size is fixed for all layers. The filter size is 1X2. Max-pooling layers are used in DeepNet to down-sample the data. Two dense layers are preserved five rounds later of convolution, batch normalisation, and layer pooling. The first layer has 16 neurons, while the second layer has eight. We discover that CNN layers can extract crucial features for identifying depression and anxiety after examining the visual representation of the 15th layer. As a result, we use less neurons in the fully connected layers.

3.6 Softmax Layer:

A softmax activation function is the final layer that forecasts the final output. As an output, the softmax function returns a vector that represents the probability distributions of a list of possible outcomes .There are two possibilities in this instance. As a result, two neurons are required to represent them [15].

3.7 Test Result:

The inference procedure was created to see if the established model could correctly identify a given EEG signal from a random dataset. The inference method was loaded with the the DeepNet, a CNN-based DL model contained in the file. It then loads an EEG dataset, which could include normal, Depression, or anxiety patients. The proposed The DeepNet, a CNN-based DL model did not produce the promised output, which makes it rather untrustworthy. Positive results are occasionally obtained using the proposed model The DeepNet, a CNN-based DL model and vice versa.

Conclusion

This research successfully use Deep Learning models to analyse EEG data and demonstrate the modification of brain processes in depression and anxiety. The Proposed DeepNet, a CNN-based DL model developed in this study, outperforms the other baseline approaches, it may be concluded. At the point when record wise split information is considered, precision of 0.9837 and AUC of 0.989 are reached. While utilizing subject wise split information, an exactness of 0.904 and an AUC of 0.946 were found. These discoveries induction that a CNN prepared on record wise split information becomes prepared when applied to EEG information with few people. However, the majority of past research provided in for the training and testing of their models, used record wise split data [16]. At the DeepNet level, the network is also able to distinguish between the normal, depressed and anxiety classes. In non-anxiety participants, the value of left electrodes placed is higher than the value of right electrodes placed, according to the activation maps of DeepNet last layer, and the value of right electrodes placed is higher than the value of left electrodes placed in anxiety subjects. In non-anxiety patients, the value of right electrodes is greater than the value of left electrodes, while in anxiety subjects, the value of right electrodes placed is greater than the value of left electrodes placed. Furthermore, the authors accept that depression affects both right and left side hemispheres of the brain in various ways. The Research of this study are quite promising, and this work can be expanded in the future by taking into account different elements.

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Confereces

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