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DeprNet: A Deep Convolution Neural Network Framework for Detecting Depression Using EEG

Ms.M.Bhargavi[1], Kambam Rohith[2], Venganti Sreeja[2], M Vijay Kumar[2], CH Kranthi [2][1]Asst. Professor,Computer Science and Engineering, CMR Engineering College, medchal, T.S, India[2]B.Tech, Computer Science and Engineering, CMR Engineering College, medchal, T.S, India

Abstract: An upsurge in suicide instances throughout the globe is often caused by depression. Therefore, a precise diagnosis and therapy are required to lessen the consequences of depression. The electrical activity of the brain is measured and recorded using an electroencephalogram (EEG). It may be used to provide an accurate assessment on the severity of depression. Previous research established the viability of using deep learning (DL) models with EEG data to diagnose mental disorder. The L-based convolutional neural network (CNN) named DeprNet is therefore suggested in this research as a means of identifying the EEG data of depressed and healthy patients. The Patient Health Questionnaire 9 score is utilised in this instance to indicate how severe the depression is. This paper presents the performance of DeprNet in two trials, namely the recordwise split and the subjectwise split. When recordwise split data are taken into account, the results obtained by DeprNet have an accuracy of 0.9937 and an area under the receiver operating characteristic curve (AUC) of 0.999. However, when subjectwise split data are used, an accuracy of 0.914 and an AUC of 0.956 are achieved. These findings imply that CNN overtrains on EEG data with a limited number of individuals when trained on recordwise split data. Comparing DeprNet's performance to the other eight baseline models, it is impressive. Additionally, while viewing the final CNN layer, it is discovered that for depressed people, the values of the right electrodes are dominant, but for normal subjects, the values of the left electrodes are significant.

1. INTRODUCTION

Mental illness, usually referred to as mental health diseases, is a medical condition of the brain that may have an impact on one's thoughts, actions, and emotions. Additionally, it causes a lack of interest and energy, may have a negative impact on relationships and job performance, and raises the risk of suicide.

Each year, over 13% of children, 46% of teenagers, and 19% of adults battle with mental illness worldwide [1]. Therefore, early identification of depression is essential to preserve the lives of depressed people by preventing it from progressing to a severe and irreparable condition. Usually, the patient's behaviour exhibits the signs of depression. As a result, physicians employ questionnaires and talking therapy sessions as screening tools to gauge the severity of depression. However, the effectiveness of the counsellor or psychiatrist will determine how well the talking session goes. In addition, individuals who are sad are less likely to ask for assistance since mental illness is stigmatised. As a consequence, a significant proportion of those who are depressed do not get the optimum treatment and enough recovery time. Therefore, developing appropriate and effective methods for diagnosing depression is a developing topic of research, and recent advancements in instrument or sensor technology bring up new avenues for doing so. Electroencephalogram (EEG) is a portable technique that may record the electrical activity of brain neurons from the scalp surface in real time, together with magnetoencephalography, magnetic resonance imaging, functional magnetic resonance imaging, and physiological data. Due to the fact that the parietal lobe of the human brain produces an EEG signal that is associated to cognitive tasks and emotional states [2] it has been noticed that the majority of cognitive behaviour and psychological activities are examined by EEG [3]. Consequently, the EEG signal might be used to detect mental disease and comprehend human cognition. Visual interpretation of complicated, nonlinear, and nonstationary EEG signals is challenging.

A Description Of The Project:

Additionally, extracting task-relevant characteristics from the EEG output is a laborious process. Naturally, linear approaches are unable to detect the intricate dynamic changes in the EEG data. In order to extract characteristics from the EEG data for computer-aided diagnosis (CAD) of depression, deep learning (DL)-based algorithms might be applied. because DL-based approaches can automatically and with little to no effort extract exceedingly complex and highly nonlinear features from raw data.

Researchers in the fields of cognitive science, psychology, and neuroscience have thoroughly examined EEG data from many angles. However, Craik et al. [4] found that 14% of the prior research utilised automated artefact removal methods, 49% manually eliminated artefacts, and 37% did not preprocess the EEG data. The research also showed that 20% of earlier studies utilised pictures that were created by transforming EEG data into images, 41% of earlier studies used computed features, 39% of earlier studies used signal values. Additionally, 53% of models for network design were based on convolutional neural networks (CNNs), 18% on deep belief networks (DBNs), 10% on recurrent neural networks (NNs), 11% on multilayer perceptron models, and the remaining 8% on stacked autoencoders. According to the report, CNN is the preprocessing method of choice for researchers working with EEG data since it requires less processing.

2. LITERATURE SURVEY

2.1 Existing System

With improved probabilistic NN, Ahmandlou et al. [5] [6] took use of nonlinear characteristics, wavelet filter banks, and fractal dimensions. They found that patients with major depressive disorder (MDD) have more complex left, right, [7] [8] and total frontal lobes of the brain than those without MDD in the beta and gamma subbands of Higuchi's fractal dimensions.[9] [10] Nonlinear characteristics are substantially useful for analysing EEG data, according to Hosseinifard et al. [11]. They examined three machine learning techniques, namely logistic regression, linear discriminant analysis, and k-nearest neighbour (KNN for classification), using a large data set of EEG recordings from 90 participants (45 normal and 45 depressed). They showed that the correlation dimension, among nonlinear properties, was a useful feature for analysing EEG data and differentiating depressed from non-depressed people. A model that combines linear and nonlinear characteristics may, however, provide higher identification accuracy. In order to compare the findings from the left electrodes and the right electrodes, Faust et al. [12] used PNN to use wavelet packet decomposition and other nonlinear properties. Additionally, they contrasted the output of seven conventional categorization methods. Despite the models' high degree of accuracy, the methodologies have several shortcomings. This research neglected the stage of feature selection and did not take feature redundancy into account. Additionally, since the data were split into training and testing groups in a recordwise way, the stated high accuracy may be the product of overfitting. Additionally, Acharya et al. [13] created a depression diagnostic index using nonlinear approaches and a support vector machine (SVM) for classification. Additionally, they created a depression diagnostic index by carefully combining the nonlinear properties. The use of the depression diagnostic index for categorization is debatable since there is no proof that the nonlinear characteristics employed in the research to define it are related to depression. Similar research was done utilising three-electrode ubiquitous EEG collectors on 178 participants by Cai et al. [14]. The DBN outperforms the conventional shallow models, according to this research [15]. The model demonstrated the viability of using a tiny widespread EEG collector for the identification of depression while having an accuracy rate of just 78.24%. The method's performance should also be evaluated on additional electrodes in order to determine how generalizable it is. Alpha interhemispheric asymmetry and power of frequency bands were used with SVM by Mumtaz et al. [16]. Numerous additional scientists investigated the significance of alpha asymmetry and the efficacy of various frequency bands in identifying depression. Principal component analysis and SVM were utilised by Liao et al. [17] to extract features.

2.2Proposed System

The research makes it apparent that two feature extraction techniques—manual and automatic—were largely investigated for detecting depression using EEG. But the stated accuracy by the majority of earlier investigations is not adequate. Thus, actual use of these approaches is not possible. Due to the fact that single-channel raw EEG data were used as the network's input in earlier experiments utilising DL models, the spatial information needed for classification was entirely omitted [18]. However, by choosing the hyperparameters of the architecture, CNN-based algorithms' performance may be enhanced [19]. It encourages us to continue working in this way. In order to achieve high classification accuracy, this work tries to construct a straightforward CNN that takes into account both spatial and temporal information. Understanding the function of the left and right hemispheres of the brain's activities for the categorization of depression is made easier by the straightforward network architecture. The following is a summary of the key contributions made by the suggested study.[20]

1) Based on four-second EEG recordings from 19 channels, a new CNN architecture named DeprNet is developed for distinguishing depressed and healthy people. The implementation

of the suggested strategy in real-world situations is made easier by the use of brief EEG recordings.

2) The accuracy obtained in this research, which has 17 307 samples, is 0.914, the best among comparable CNN-based designs. Due to the accuracy paradox, additional quantitative classification metrics, such as precision, recall, and F1-score, are also taken into account when comparing the performance of the suggested technique with the outcomes of various state-of-the-art systems.

3) This research also shows that depression has distinct effects on the right and left hemispheres of the brain in terms of how they function. This conclusion is reached by looking at and visualising the last layer of the proposed CNN, which demonstrates how, in determining the degree of depression, this layer utilises the values of the right electrodes for depressed participants and the left electrodes for non-depressed subjects.

2.2 Details of the Data Set

Because the effects of depression are evident in the resting state, we used 33 patients' 9-minute long resting-state EEG recordings for this investigation. 18 of the 33 participants are healthy, and 15 of the subjects are sad. Additionally, each subject's Patient Health Questionnaire 9 (PHQ-9) score is calculated after an interview and after seeing a psychologist. When creating the data set, 19 channels with the average of the ear electrodes (A1 and A2) as common references were taken into consideration in accordance with the 10-20-electrode placement scheme (as illustrated in Fig. 1)

A 0.1-Hz high-pass filter, a 100-Hz low-pass filter, and a 50-Hz notch filter are all taken into account during recording in order to, respectively, filter out low-frequency noise, irrelevant signals, and baseline noise. To identify and eliminate eye movement artefacts, the independent component analysis (ICA) is used to signals of the open eye state [21]. The ICA makes the assumption that the signal may be conceptualised as the weighted sum of non-Gaussian components that are statistically independent . Using the "runica" method with its default parameters from the EEGLAB toolbox, the ICA is applied to the signal.

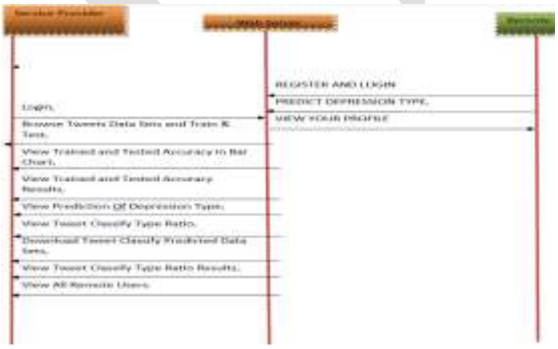

Fig 1: System Flow

3. SYSTEM ANALYSIS&DESIGN

3.1The design of DeprNet

Five convolutional layers, five batch normalisation layers, five max-pooling layers, and three fully linked layers make up the proposed CNN, called DeprNet. While all previous layers employ the leaky rectified linear unit (LeakyReLU) activation function, the final fully linked layer uses the softmax activation function. Fig. 3 depicts how these layers are arranged.

Although the network performs a 1-D convolution function, the input data are 2-D. The information related to the spatial dimension, or x-axis, is preserved when the 1-D convolution is applied to the temporal dimension, or y-axis. Understanding how spatial information is processed by the network and which channels are crucial for the identification of depression using this strategy of keeping the spatial information separate is helpful

1) Convolutional Layers: Convolution is a process used to turn a signal into useful signals. A linear, time-invariant filter that may be multiplied and translated on the input signal to produce new signal values is necessary for convolution. The input layer comes before the first convolutional layer in DeprNet. For each layer, either 128 or 64 or 32 filters are used. With a filter size of 1 5, the first three convolutional layers are convolved. The fourth and fifth convolutional layers, respectively, have filter sizes of 1 3 and 1 2. When a NN is used to accomplish convolution, a kernel/filter is slid over the input signals to produce an output that is also referred to as the layer's activation map . To extract the majority of the crucial low-level features, we choose 128 filters for C1, and we decrease the number of features as the network's depth increases in order to transform the EEG data into a low-dimensional space. Only significant, high-level relevant characteristics are present in the C5 layer.

2) Batch normalisation: This technique is used to stabilise the network by bringing the output of the preceding layer into compliance. Five batch normalisation layers are included in DeprNet, one layer after each convolutional layer.

On the output of the batch normalisation layers, the network activates LeakyReLU. When batch normalisation is used, we see a higher rate of convergence than when batch normalisation is not taken into account.

3. Pooling Layers: Max-pooling layers are used in DeprNet to down-sample the data. The temporal dimension is subject to 1-D pooling actions by the network. The filter size for each of the five layers is 1 2.

4) Fully Connected Layers: Two dense layers are preserved after five rounds of convolution, batch normalisation, and layer pooling. Eight neurons make up the second layer, whereas there are 16 in the first layer. After viewing the 15th layer's activation map, we see that CNN layers can successfully extract crucial features for identifying sadness. As a result, we use fewer neurons in the fully linked layers.

5) Softmax Layer: A thick layer with a softmax activation function makes up the last layer that forecasts the outcome.

The output of the softmax function is a vector that depicts the probability distributions of a number of possible outcomes [19]. There are two possible outcomes in this scenario, therefore we need two neurons to represent them.

3.2 System Architecture: Visualisation of Convolutional Layers' Learned Features

A NN's convolutional layers and fully connected layers are in charge of conducting classification and feature extraction, respectively. The majority of classification-related decisions rely on convolutional layers since the last three layers (16 + 8 + 2 = 26) have a minimal number of neurons. This implies that CNN's final layer may include important information about the choices the network makes when categorising the topics. As a result, this research offers a visualisation of the M5 layer's max-pooling activation map.

The network is trained on all of the data points—17 207 samples—for this study. The data points are sent forward to the network after training it to get its activation maps.

The output volume of size 193032 is acquired for each data point from layer 15, and the average of the answers over 32 filters and 30 time points is then used to create a vector of size 19.

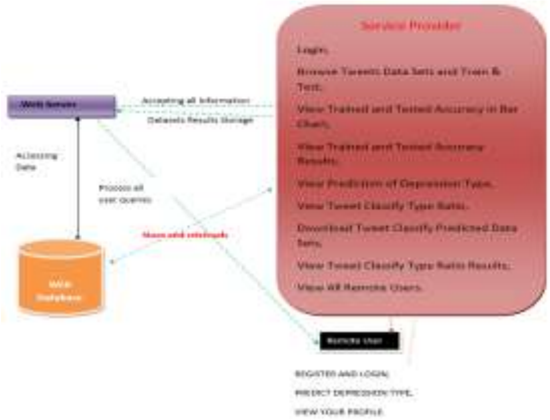

Fig 2 : System Architecture

3.4 Data Flow Diagram: Whenever a new system is developed, user training is required to educate them about the working of the system so that it can be put to efficient use by those for whom the system has been primarily designed. For this purpose the normal working of the project was demonstrated to the prospective users. Its working is easily understandable and since the expected users are people who have good knowledge of computers, the use of this system is very easy.

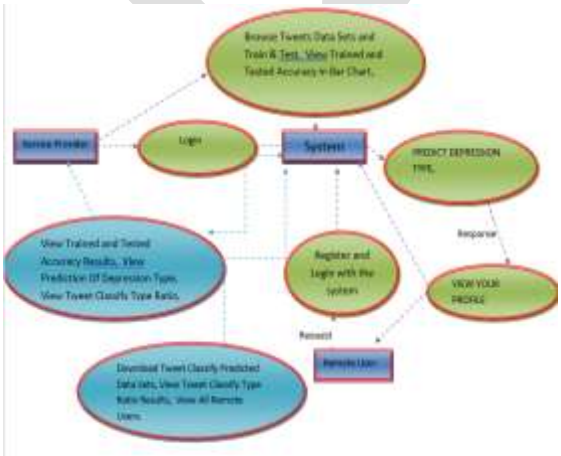

Fig 3: Data Flow Diagram

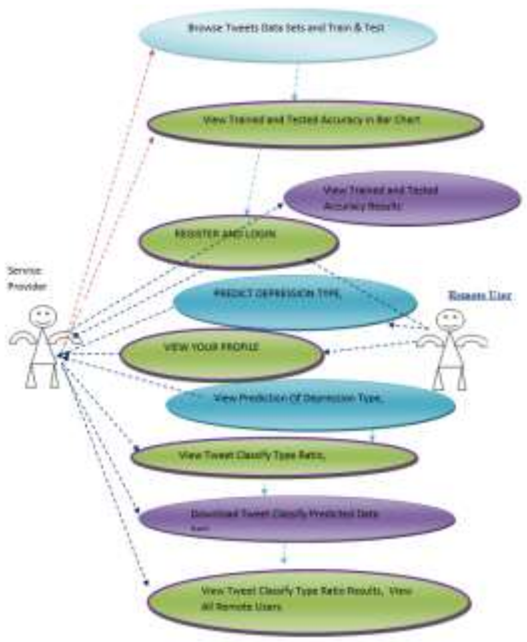

Fig 4 Use Case UML Diagrams

5. CONCLUSION

This work effectively uses DL models to analyse the EEG data and show how the brain's activity changes during depression. It can be said that the CNN-based DL model called DeprNet, which was suggested in this work, outperforms the other baseline techniques. When recordwise split data are taken into account, accuracy of 0.9937 and the AUC of 0.999 are obtained. Subject-wise split data are used, and accuracy of 0.914 and AUC of 0.956 are achieved.

These findings imply that CNN overtrains on EEG data with a limited number of individuals when trained on recordwise split data. To train and evaluate their models, the majority of the earlier experiments discussed in Section II used recordwise split data. Additionally, it has been noted that at the DeprNet level itself, the network is capable of differentiating between the normal and depressed classes. According to the activation maps of DeprNet's last layer, in nondepressed participants, left electrode values are greater than right electrode values, while in depressed people, right electrode values are greater than left electrode values. The authors also contend that depression has distinct effects on the functions of the two hemispheres of the brain.

6. FUTURE SCOPE

The findings of this research are quite encouraging, and this work may be expanded in the future by taking a variety of aspects into account. A customised mobile phone application may also be created based on the suggested diagnostic process to display a patient's state of depression in real time.We then average all of the data points that correspond to a subject's replies before creating response vectors with 19 values for each subject. For each participant, the approach described above provides the average values of 19 channels of filtered data (filtered from all convolutional layers). These numbers may help identify the channels most likely to cause depression. These response vectors are displayed as heat maps for better exposition. The left-side, right-side, and centre electrodes, respectively, are represented by eight, eight, and three of these 19 values.

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