A DEEP CONVOLUTION NEURAL NETWORK FRAMEWORK FOR DETECTING DEPRESSION USING EEG

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ABSTRACT— Depression is a common reason for an increase in suicide cases worldwide. Thus, to mitigate the effects of depres- sion, accurate diagnosis and treatment are needed. An electroen- cephalogram (EEG) is an instrument used to measure and record the brain's electrical activities. It can be utilized to produce the exact report on the level of depression. Previous studies proved the feasibility of the usage of EEG data and deep learning (DL) models for diagnosing mental illness. Therefore, this study proposes a DL-based convolutional neural network (CNN) called DeprNet for classifying the EEG data of depressed and normal subjects. Here, the Patient Health Questionnaire 9 score is used for quantifying the level of depression. The performance of DeprNet in two experiments, namely, the recordwise split and the subjectwise split, is presented in this study. The results attained by DeprNet have an accuracy of 0.9937, and the area under the receiver operating characteristic curve (AUC) of 0.999 is achieved when recordwise split data are considered. On the other hand, an accuracy of 0.914 and the AUC of 0.956 are obtained, while subjectwise split data are employed. These results suggest that CNN trained on recordwise split data gets overtrained on EEG data with a small number of subjects. The performance of DeprNet is remarkable compared with the other eight baseline models. Furthermore, on visualizing the last CNN layer, it is found that the values of right electrodes are prominent for depressed subjects, whereas, for normal subjects, the values of left electrodes are prominent.

Index Terms— Convolutional neural network (CNN), electroen- cephalography, measurement of depression, pattern classification, visualization.

I. INTRODUCTION

MENTALillness, also known as mental health disorders, is a physical illness of the brain that might affect the thinking process, behavior, and mood. It also leads to loss of interest and energy, may cause adverse effects on relationships, performance at the workplace, and increase the risk of suicide. Worldwide, almost 13% of the child population, 46% of adolescents, and 19% of the adult population struggle with mental illness each year Thus, the diagnosis of depression in the early curable stages is crucial to prevent it from reaching a severe and irreversible state and to save the life of depressed individuals. Generally, the symptoms of depression are reflected in the behavior of the patient. Hence, doctors conduct talking sessions and use questionnaires as screening tools for determining the level of depression. However, the out- come of a talking session is dependent on the psychiatrist's or counselor's proficiency. Moreover, depressed patients are less likely to seek help due to the stigma attached to mental illness. As a result, a significant number of depressed indi- viduals do

not get the best possible medication and sufficient revival time. Thus, finding suitable and efficient approaches for detecting depression is an emerging field of study, and the recent developments in the instrument or sensor technology open up new horizons to diagnose depression. Among elec- troencephalogram (EEG), magnetoencephalography, magnetic resonance imaging, functional magnetic resonance imaging, and physiological data, EEG is a portable technology that can capture the electrical activity of brain neurons from the scalp surface in real time. It is observed that most of the cognitive behavior and psychological activities are analyzed by EEG because the EEG signal acquired from the parietal lobe of the human brain is related to the cognitive tasks and emotional states . Thus, the EEG signal could be exploited in order to understand the human cognitive process and diagnose mental illness. However, it is difficult to interpret nonstationary, nonlinear, and complex EEG signal visually. Moreover, it is a tedious task to fetch task-relevant features from the EEG signal. Naturally, linear methods cannot observe the complex dynamic variations in the EEG signal. Therefore, the deep learning (DL)-based approaches could be used to extract features from the EEG signal for computer-aided diagnosis (CAD) of depression because DL-based methods can extract extremely complex and highly nonlinear features automatically from raw data with little or no effort

Neuroscience, psychology, and cognitive science researchers have analyzed EEG data extensively in various aspects. However, Craik *et al.* [4] revealed that 37% of the previous studies did not preprocess the EEG data, 49% removed artifacts manually, and 14% used automatic artifact removal techniques. The study also presented that 41% of previous studies considered calculated features, 39% employed signal values, and 20% used images, which were transformed from EEG data as input data for the network. In addition, for network architecture, 53% exploited convolutional neural network (CNN)-based models, 18% explored the deep belief network (DBN), 10% used the recurrent neural network (NN), 11% employed multilayer perceptron-based models, and rest 8% considered the stacked autoencoder. The study suggested that, due to less preprocessing, CNN is the favorite choice of the scholars dealing with EEG data.

II. LITERATURE SURVEY

A) A. SWETAA, R. GAYATHRI, AND V. V. PRIYA, "AWARENESS OF MENTAL HEALTH AMONG TEENAGERS," *DRUG INVENTION TODAY*, VOL. 11, NO. 8, PP. 1979–1982, 2019.

Depression is a common psychiatric disorder, which causes significant patient distress. Bipolar disorder is characterized by mood fluctuations between depression and mania. Unipolar and bipolar depression can be easily confused because of similar symptom profiles, but their adequate treatment plans are different. Therefore, a precise data-driven diagnosis is essential for successful treatment. In order to aid diagnosis, research applied machine learning to brain imaging data, in particular to electroencephalography (EEG), with accuracies reaching 99.5% (unipolar vs. healthy) or 85% (bipolar vs. healthy). However, these results arise from small training sets, without validation on independent data, and thus have a high risk of inflated accuracies due to data over-fitting. We propose to use a bigger corpus of realistic clinical data for training and testing and improve classification with microstates features, which can assess the function of large-scale brain networks

B) M. A. BELL AND K. CUEVAS, "USING EEG TO STUDY COGNITIVE DEVELOPMENT: ISSUES AND PRACTICES," *J. COGNITION DEVELOP.*, VOL. 13,

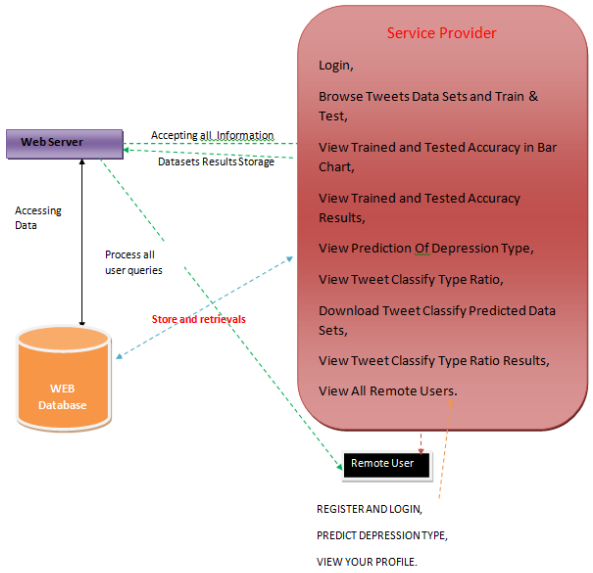
NO. 3, PP. 281–294, JUL. 2012.

Nearly 264 million people around the globe currently suffer from clinical depression, according to the World Health Organization. Although there are diagnostic techniques and treatments presently used by professionals, they are not always helpful. Herein, we suggest the use of advanced technological methods to diagnose depressed patients correctly. A machine learning approach is presented, which uses the electroencephalogram for diagnostics. The model extracts multiple features by applying a continuous wavelet transform (CWT) for each recording. These recordings are employed to train and test the model, with data gathered from 15 depressed and 15 normal patients. After the features are extracted from these recordings, it is organized into matrix form. The features are dimensionally reduced using kernel-principal component analysis and principal component analysis techniques, ranked using Student's t-test, and then labelled as normal or depressed with various classifiers. Accuracies of 99.33% and 99.13% were achieved for the right and left hemispheres of the brain, respectively, and 99.26% for the combined hemispheres of the brain. As compared to the discrete and empirical wavelet transform feature extraction methods, the CWT attained the best results. A depression severity index was also developed, using two features for discriminating the classes: normal versus depressed.

C) H. W. COLE AND W. J. RAY, “EEG CORRELATES OF EMOTIONAL TASKS RELATED TO ATTENTIONAL DEMANDS,” *INT. J. PSYCHOPHYSIOL.*, VOL. 3, NO. 1, PP. 33–41, JUL. 1985.

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.

III. PROPOSED SYSTEM



Modules

Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Login, Browse Data Sets and Train & Test, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View All Antifraud Model for Internet Loan Prediction, Find Internet Loan Prediction Type Ratio, View Primary Stage Diabetic Prediction Ratio Results, Download Predicted Data Sets, View All Remote Users.

View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT PRIMARY STAGE DIABETIC STATUS, VIEW YOUR PROFILE.

CONCLUSION

This study successfully makes use of DL models for ana- lyzing the EEG data and demonstrating the transformation of brain activities in depression. It can be concluded that the DeprNet, a CNN-based DL model proposed in this study, performs better than the other baseline methods. Accuracy of 0.9937 and the AUC of 0.999 are achieved when recordwise split data are considered. Accuracy of 0.914 and the AUC of 0.956 are obtained, while subjectwise split data are adopted. These results suggest that CNN trained on recordwise split data gets overtrained on EEG data with a small number of subjects.Section II employed recordwise split data for the training and testing their models. It is also observed that the network can distinguish both the normal and depressed classes at the DeprNet level itself. The activation maps of the last layer of DeprNet suggest that the value of left electrodes is more than the values of right electrodes in nondepressed subjects, and the value of right electrodes is more than the values of left electrodes in depressed subjects. Moreover, the authors believe that depression affects the activities of both the hemispheres of the brain differently. The results obtained in this study are very promising, and this work can be extended by considering multiple factors in the future. Furthermore, based on the proposed diagnosis pipeline, a personalized mobile phone application can be developed to show the real-time depression level of a patient.

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