International Journal of All Research Education and Scientific Methods (IJARESM), ISSN: 2455-6211
Volume 11, Issue 4, April-2023, Impact Factor: 7.429, Available online at: www.ijaresm.com

DeprNet:Depression Detection by Using a Deep ConvolutionNeural Network Framework Using EEG

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ABSTRACT

Depression is a common reason for an increase in suicide cases world-wide.An electroencephalogram (EEG) is an instrument used to measure and record the brain's electrical activities. This study proposes a DL-based convolutional neural network (CNN) called DeprNet for classifying the EEG data of depressed and normal subjects.The performance of DeprNet in two experiments, namely, the record-wise split and the subject-wise split, is presented in this study. These results suggest that CNN trained on record-wise 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

Keywords: Measurement of Depression, Pattern visualization, Classification, Convolutional neural network (CNN), Electroencephalograph.

I. INTRODUCTION

A prevalent factor in the rise in suicide cases worldwide is depression.The electrical activity of the brain is measured and recorded using an electroencephalogram (EEG). The DeprNet convolutional neural network (CNN) is proposed in this paper to classify the EEG data of depressed and healthy patients.In this study, the effectiveness of DeprNet in two experiments—the record-wise split and the subject-wise split—is given. These findings imply that CNN overtrains on EEG data from a small number of subjects after being trained on record-wise split data. Comparing DeprNet's performance to the other eight baseline models, it is impressive.

We have been able to investigate new approaches for identifying and diagnosing depression using electroencephalography (EEG) data thanks to the development of deep convolution neural networks (DCNNs). We can extract more pertinent and significant features from EEG data with the aid of DCNNs, which can subsequently be utilised to precisely identify depression. A DCNN-based system for depression identification utilising EEG data is presented in this research. A fully connected layer for classification is placed after several layers of convolutional and pooling layers. The framework's performance is assessed using a publiclyaccessible dataset and contrasted with that of other current methodologies. The findings demonstrate that the suggested framework outperforms the current methods in terms of accuracy and F1 scores. Additionally, the proposed framework is proved to be reliable.

The research makes it clear that two feature extraction techniques—manual and automatic—were primarily investigated for detecting depression using EEG. But the stated accuracy by the majority of earlier investigations is not adequate. As a result, these methods 3 cannot be used in real-world situations. As single-channel raw EEG data were used as the input for the network in earlier experiments utilising DL models, the spatial information for categorization was completely missing. However, by choosing the proper parameters of the architecture, CNN-based algorithms' performance can be enhanced. It encourages us to continue working in this direction. In order to achieve high classification accuracy, this study tries to construct a straightforward CNN that takes both spatial and temporal information into account. Understanding the function of the left and right hemispheres of the brain's activities for the classification of depression is made easier by the straightforward network architecture. The following is a list of the key contributions made by the suggested study.

Researchers in the fields of neuroscience, psychology, and cognitive science have thoroughly examined EEG data from many angles. However, Craik et al. found that 14% of the prior research utilised automatic artefact removal methods, 49% manually eliminated artefacts, and 37% did not preprocess the EEG data. The study also showed that 20% of earlier studies used images that were created by transforming EEG data into images, 41% of earlier studies used computed features, 39%

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. CNN is the preferred option, according to the study, because there is less preprocessingThese methods have several limitations due to the lack of automation and reliance on manual feature selection, even if they are generally effective at detecting depression. Deep learning has gained popularity recently as a method for EEG-based depression identification because of its capacity to automatically extract important features from the EEG signals. Since they can capture the temporal changes of EEG signals and extract pertinent characteristics from the data, DCNNs are particularly well suited for this purpose. Convolutional long short-term memory networks, temporal convolutional networks, and convolutional recurrent neural networks are some of the DCNN architectures that have been suggested for identifying depression from EEG signals.

II. RELATED WORK

First Notable ContributionFeld moved from Pusankatil and Joseph in 2012 She considered 15 depressed subjects and she considered 15 non-depressed subjects.Training a two-layer feedforward artificial NN. You used them allFrequency range of EEG signals for relative extraction Wavelet energy and signal entropy based functions. ever sinceis a preliminary study, where a small feature set and conventional machine learning techniques were used for classification. In the same year, Ahmandlou et al. ExploitedNonlinear functions, wavelet filter banks, fractal dimension Use an extended probabilistic NN. Higuchi's grades The fractal dimensions are left, right, Frontal and total frontal lobes of the brain of key people Beta major depressive disorder (MDD) versus non-MDD and gamma subbands. Hosseinifard et al. Also check nonlinear features are very effective for analysisEEG data. They used a large dataset of electroencephalographyTesting and comparison of 90 subjects (45 normal, 45 depressed) three machine learning algorithms namely logistic regression, linear discriminant analysis and k nearest neighbors (ANN) classification. Among the nonlinear features, theyCorrelation dimension was a powerful feature of analysisEEG signals that distinguish between depressed and non-depressed statessubjects. However, using a model that combines linear and nonlinear features may improve detection accuracy. Fist and others. [12] Exploited wavelet packetization, etc.We compared the nonlinear features with the PNN and compared the left electrodeCorrect electrode results. They also compared theirResults of seven classical classification algorithms. apart fromDue to the high accuracy of the model, there are some drawbacksmethod. This study did not consider the following redundancies: Selected a feature and ignored the feature selection.

Additionally, Acharya et al. created a depression diagnosis index using nonlinear approaches and a support vector machine (SVM) for classification.Additionally; they created a depression diagnosis index by carefully combining the nonlinear properties. The use of the depression diagnosis index for categorization is debatable because there is no proof that the nonlinear features employed in the study to define it are related to depression. Similar research was done on 178 participants by Cai et al. using three-electrode ubiquitous EEGcollectors. The DBN outperforms the conventional shallow models, according to this study [14]. Despite the model's accuracy of 78.24%, it demonstrated the viability of using a modest widespread EEG collector.

Alpha inter hemispheric asymmetry and power of frequency bands were used with SVM by Mumtaz et al. Numerous other researches 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. to extract features. With the bagged tree, Bairy et al. utilised linear prediction coding. Sharma et al.'s investigation into the function of SVM and handmade features. The KNN classifier produced the best results when Cai et al. compared the classification performance of four algorithms using data from 213 patients.The 11-layer proposed model was comprised of a convolutional neural network which was included two Conv2D layers with ReLU activation function, two Max-pooling layers, and one dropout layer, fully connected layer which was contained two dense layers with ReLU activation function and one dropout, and the output layer as the last section was composed of one dense layer with ReLU activation function. It also utilized ten-fold cross-validation to evaluate and verify the result of the model. As a result, it obtained a high accuracy compared The eleven-layer proposed model included a convolutional neural network with two Conv2D layers with ReLU activation function, two Max-pooling layers, one dropout layer, a fully connected layer with two dense layers with ReLU activation function, one dropout layer, and an output layer made up of one dense layer with ReLU activation function as the final section. Additionally, ten-fold cross-validation was used to assess and confirm the model's output. As a result, it achieved a high level of accuracy.

III. METHODOLODGY

Because the effects of depression are reflected in the resting state, we used 33 patients' 9-minute long resting-state EEG recordings. 18 of the 33 subjects 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 mean of the ear electrodes (A1 and A2) as common references are taken into account in accordance with the 10-20-electrode positioning scheme.

In order to isolate and remove eye movement artefacts from signals of the open eye state, independent component analysis (ICA) is used. The ICA makes the assumption that the signal can be conceptualised as the weighted sum of non-Gaussian statistically independent components. The "runica" algorithm from the EEGLAB toolbox is used with its default settings to apply the ICA to the signal. A total of 17 310-s of EEG recording from all subjects' data are taken into consideration for further analysis after preprocessing.The data is divided into 17 307 data points, and two data matrices are created withdistinct dimensions: 17 307 19 1.024 and 17 307 1. The input data matrix in the first matrix is different from the output data matrix in the second matrix (enclosed class).In the input data matrix, each data point has data of 4 s (with 75% overlapping) and 19 channels.

According to the literature, two feature extraction methods—manual and automatic—were mainly investigated for detecting depression using EEG. However, the accuracy levels reported by the majority of earlier investigations are unsatisfactory. This makes these techniques unsuitable for actual application. As single-channel raw EEG data were used as the network's input, previous studies utilising DL models completely ignored the spatial information for the categorization. However, by choosing the architecture's hyperparameters, CNN-based algorithms can perform better. It spurs us on to continue in this direction. The goal of this study is to create a straightforward CNN that, in order to achieve high classification accuracy, takes into account both spatial and temporal information.

1) Short EEG recordings of 4 s from 19 channels are used to distinguish sad and normal participants using a unique CNN framework called DeprNet. The deployment of the suggested strategy in real-world situations is made easier by the use of brief EEG recordings.

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

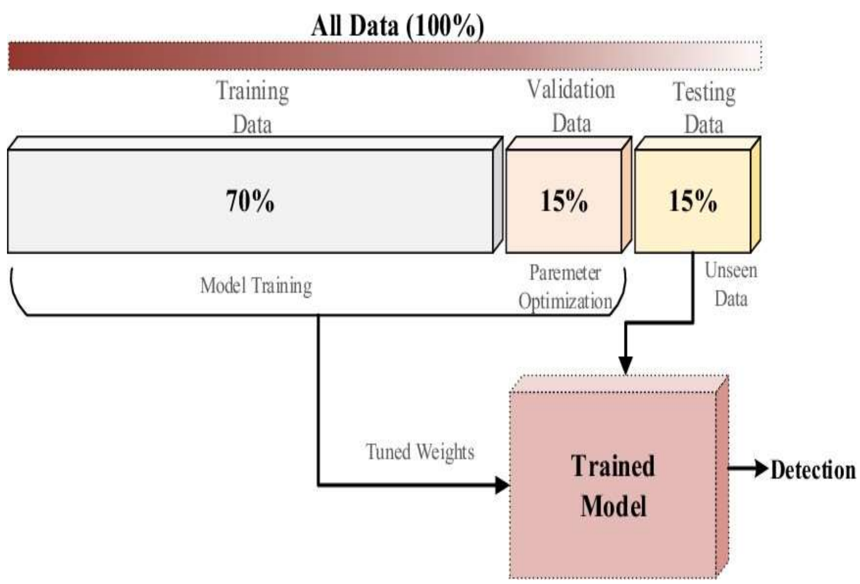

Figure-1

A. Working of Cnn Algorithm

Convolutional Neural Network is a deep learning algorithm commonly used in image recognition, but it can also be used in intrusion detection systems. The process of using CNN in an early warning intrusion detection system typically involves the following steps: Data Collection: The system collects data from various sources such as network traffic, system logs, and user behavior. Data Preprocessing: The collected data is preprocessed by removing noise, normalizing the data, and converting it into a format that can be used by the CNN algorithm.

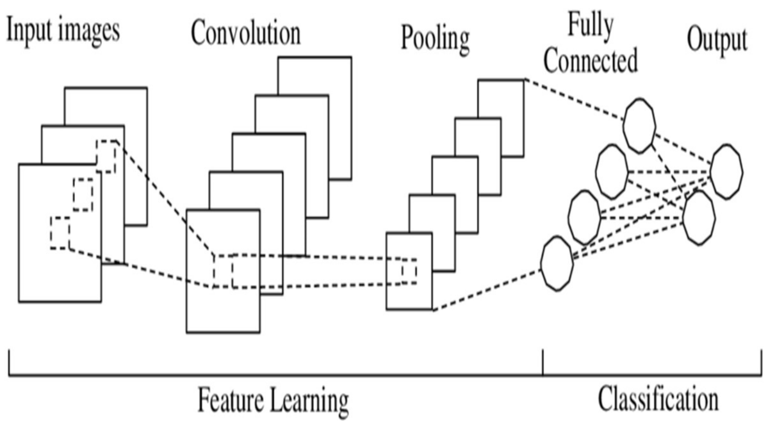

Figure-2

Feature Extraction: The preprocessed data is fed into the CNN algorithm, which automatically extracts important features from the data. Training: The extracted features and corresponding labels (indicating whether an intrusion occurred or not) are used to train the CNN algorithm. The CNN algorithm learns to identify patterns in the data that are indicative of intrusions. Testing: The trained CNN model is tested on new data to evaluate its accuracy in detecting intrusions. Early Warning: The CNN algorithm is integrated into an early warning system that analyzes incoming data in realtime. When the system detects a potential intrusion, it alerts the appropriate security personnel so that action can be taken to prevent the intrusion from succeeding. The CNN algorithm can be trained on a large dataset of labeled data to improve its accuracy in detecting intrusions. It can also be fine-tuned over time as new data becomes available. The early warning system can be further improved by integrating it with other security measures such as firewalls, antivirus software, and access control systems

IV. SYSTEM ARCHITECTURE

The proposed CNN, DeprNet, consists of five convolutional layers, five batch normalization layers, five max-pooling layers, and three fully connected layers. The last fully connected layer uses softmax activation function, while all other layers use leaky rectified linear unit (LeakyReLU) activation function. The details of parameters and filters are reported in Table Even though the input data are 2-D, the network performs a 1-D convolution operation. The 1-D convolution is applied on the time dimension, i.e., y-axis, and it ensures that the information associated with the spatial dimension, i.e., x-axis, remains as it is.

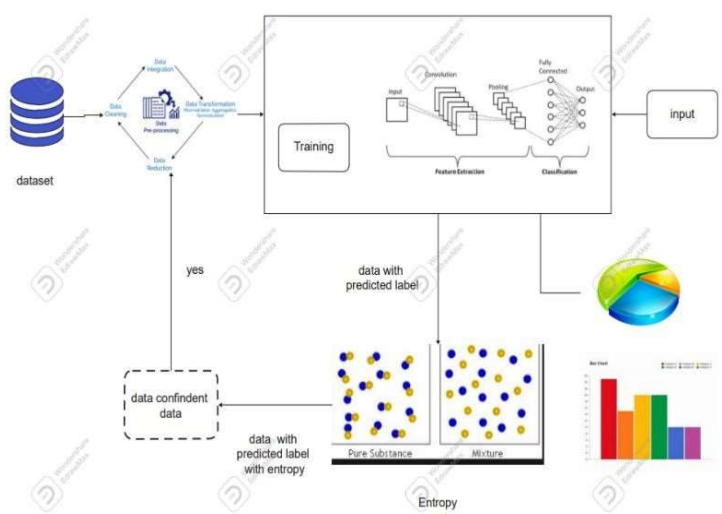

Figure-3

V. CONCLUSION & FUTURE SCOPE

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 record wise split data are taken into account, accuracy of 0.9937 and AUC of 0.999 are obtained. While subject-wise split data are used, accuracy of 0.914 and the AUC of 0.956 are obtained. These findings imply that CNN overtrains on EEG data from a small number of subjects when trained on record-wise split data. However, the majority of the earlier investigations discussed in Section used split data by record for building and testing their models. Additionally, it has been noted that the network, even at the Depr Net level, can distinguish between the normal and depressed classes.The findings of this study are quite encouraging, and this work can be expanded in the future by taking a variety of aspects into account. A customised mobile phone application can also be created based on the suggested diagnosis pipeline to display a patient's real-time depression level.

Expanding the dataset utilised in the study to include more varied people with different demographic backgrounds, such as age, gender, and cultural origins, is one potential avenue for future research. This would boost the model's applicability to various groups and aid to assure generalizability. Examining the application of DeprNet in actual clinical settings, such as primary care practises or community mental health centres, is another possible area for future study. This might entail carrying out studies to assess the viability and efficacy of utilising DeprNet as a depression screening tool in such contexts.

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