A Deep Convolution Neural Network Based Model for Identification Depression Using EEG

SUMESHWAR SINGH , Department of Comp. Sc. & Info. Tech., Graphic Era Hill University, Dehradun, Uttarakhand, India 248002,

ABSTRACT

An upsurge in suicide instances throughout the world is frequently caused by depression. Therefore, a precise evaluation and counselling are essential to alleviate the consequences of depression. The electrical activity of the brain is monitored and documented using an electroencephalogram (EEG). It is capable of producing a reliable evaluation of the degree of depression. Prior investigation established the viability of using deep learning (DL) models with EEG data to diagnose mental disorder. The patient's behaviour exhibits the signs of depression. As a result, doctors employ questionnaires and talking sessions as screening methods to determine the severity of depression. DeprNet is a DL-based Convolutional Neural Network that this research suggests be used to categorise the EEG data of healthy and depressed patients. The suggested system uses a convolutional neural network as a deep learning technique. The system was created using an EEG dataset for depression, and it analyses if a subject is positive, negative, or neutral. The confusion matrix, accuracy, precision, recall, and f1-score are among the experimental findings.

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1. INTRODUCTION

Mental illness, usually referred to as mental health diseases, is brain disorder that can have an impact on one's thoughts, actions, and mood. Additionally, it causes a lack of interest and energy, may have a negative impact on relationships and work 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. Therefore, early identification of depression is essential to preserve the lives of depressed people by preventing it from progressing to a severe and irreparable state. Usually, the patient's conduct exhibits the signs of depression.As a result, doctors employ questionnaires and talking therapy sessions as assessment techniques to measure severity of depression. Even though, effectiveness of the counsellor or psychiatrist will determine how well the talking session goes. Furthermore, because of the mental health stigma that surrounds it, sad people are less likely to seek treatment. As a result, a sizable proportion of those who are depressed do not receive the optimum care and enough time to recovery. And hence, developing acceptable techniques that are effective for diagnosing depression is a developing subject of research, and current advancements in tool or sensor technology bring up new avenues to doing so. A portable device called an electroencephalogram may record in real time the electrical activity of brain neurons on the surface of the scalp, together with magneto encephalography, physiological information, functional magnetic resonance imaging, and magnetic resonance imaging. Because the human parietal lobe's EEG signal is connected to both cognitive functions and emotional states, it has been discovered that EEG is used to investigate the bulk of cognitive behaviour and psychological activity. Therefore, EEG signal might be used to detect mental disease and comprehend human cognition. Visual interpretation of complicated, nonlinear, and non-stationary EEG signals is challenging. Additionally, extracting task-relevant characteristics from the EEG output is a laborious process.Of course, linear approaches are unable to detect the intricate dynamic changes in the EEG signal. Because DL-based algorithms can automatically derive exceedingly complicated as well as quite nonlinear properties from original information with lagging or missing human intervention, they might be utilised to derive properties from EEG signal for Computer-Aided Diagnosis of depression. Researchers in the fields of cognitive science, psychology, and neuroscience have thoroughly examined EEG data from many angles. However, it was discovered that 49% of the prior research manually eliminated artefacts, 37% employed automatic artefact removal methods, and 37% did not preprocess the EEG data. The research also revealed 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.Our project's primary goal is to accurately categorise and forecast depression, to put deep learning into practise for improved performance, to enhance the use of brain signals in emotion depression and to improve performance as a whole.

2. LITERATURE SURVEY

A major contributor to the global illness burden today, depression is predicted to overtake all other diseases in the globe by 2030. A patient-friendly, affordable strategy based on readily quantifiable objective indications is necessary for early detection of depression. For the purpose to identify depression, this research analyzes multiple single-channel electroencephalographic (EEG) markers. 13 outpatient depressives without medication and 13 controls of the same gender and age had EEG recordings. Applying leave-one-out cross-validation and logistic regression analysis, classification accuracy among depressed and control participants were determined. For each EEG channel, different calculations were made. The results of all calculations showed a rise with depression. For linear and nonlinear measures, respectively, with a single measure the maximum testing accuracy was 81% and 77%. The findings of this pilot study demonstrate that depression may be distinguished while analysing multichannel EEG data using single-channel EEG analysis using a combo of measures. The results of the study demonstrate that there is no one best method for identifying depression [1].

Nigeria ultimately joined the League of the GSM nations in August 2001, however after less developed African nations like Botswana, Mozambique, Uganda, and Tanzania. The Global System of Mobile Communication was introduced in Nigeria at that time. After fourteen years, concerns have been raised about why customers to epileptic services are being shortchanged and cheated out of their money. This results from a wide range of issues, including network delivery issues and congestion. This essay explores the development of GSM services in Nigeria during the past fourteen years, the variety of services offered, and the problems encountered throughout operation. Not to mention the advantages it has given economy of Nigeria. There are suggestions on how Nigeria might gain greater advantages from GSM connectivity also. According to a factsheet from the World Health Organization released in April 2016, 1 suicide occurs every 40 seconds, resulting in an average of 2,160 suicides per day and more than 800 thousand suicides per year. In addition, among those between the ages of 15 and 44, suicide is the third greatest cause of mortality worldwide. 90% of persons who die by suicide have a prior mental disorder, according to research, and there is a strong correlation between sadness and suicide.In compared to other approaches, brain wave frequency measurement in the gamma wave region performs precise categorization of health condition, but it is inefficient in detecting depression early on [2].

Epileptic networks undergo a procedure that evolves through space and time that results in epileptic seizures. Researchers evaluate the spatio-temporal correlation in characteristics derived through multichannel EEG data with the objective of establishing a universal technique for patient-specific seizure forecasting. The frequency along with temporal domain characteristics of the EEG signals are revealed using Hjorth parameters, statistical moment also the spectral band power. It is suggested to examine temporal plus spatial correlation in training data as a whole using the multi-frame 3D CNN paradigm. In testing with 16 patients using the CHB-MIT scalp EEG dataset, suggested 3D CNN model obtains a sensitivity of 85.7%, a false prediction rate of 0.096/h, and a proportion of time-in-warning of 10.5%. Findings demonstrate that for 93.7% of the patients, at a significance level of 0.05, the suggested technique was significantly better than a Poisson-based random predictor. Their tests under varied temporal restrictions demonstrate that epileptic stage durations play a significant role in seizure performance. Considering that subject-specific engineering is not required, Researchers offer a subject-specific seizure forecast technique that is resilient to imbalanced data and generalizable to any scalp EEG dataset [3].

The CK-SVM classifier's performance was then compared to that of the Linear Discriminant Analysis, Quadratic Discriminant Analysis, and conventional SVM classifiers. Outcomes via preliminary analyses applying the LDA classifier on 55 participants (24 MDD, 31 healthy controls) revealed that applies to any variations in relative EEG power, the EEG recorded during the positive emotion induction was more accurate than the resting state in terms of participant-independent classification accuracy (LOPO-CV). The CK-SVM classifier also superior than the competing classifiers in terms of LOPO-CV accuracy. The CK-SVM, utilising seven relative power characteristics collected from seven electrodes, produced the greatest accuracy (83.64%; sensitivity = 87.50%, specificity = 80.65%). Ultimately, using the CK-SVM classifier in conjunction with positive emotion induction to detect MDD from EEG data was effective.This strategy might be applied in the future to create a brain-computer interface system that would help identify MDD in clinic settings. Moreover, a low-density electrode montage (seven electrodes) might accustomed to build such a system, emphasising its usefulness [4].

Research based on electroencephalography (EEG) have focused on identifying depression through data mining techniques, but studies on moderate depression are still in their infancy, particularly in terms of effective monitoring and quantitative measure elements. This research presents a computer-aided detection system that uses convolutional neural networks to recognise moderate depression (ConvNet). Researchers employed transfer learning to build the structure of ConvNet since the CAD system used in clinical practise and the architecture of ConvNet that was developed through trial and error should both be constructed on the foundation of local databases.Researchers also examined how other EEG features, such as spectral, spatial, also temporal information, contributed to the identification of moderate depression. They discovered that the spectrum information of the EEG was crucial and that the temporal information of the EEG significantly increased accuracy. With 24-fold cross-validation, the suggested method has an accuracy of 85.62% for identifying moderate depression and normal controls (Subject-based division of the training and evaluation sets). The technique may therefore be used in the therapeutic setting to quickly, accurately, and objectively diagnose moderate depression.Not only may testing for this approach be expensive and time-consuming. The deterioration mechanism model is quite accurate, however it requires a lot of numerical calculations and has an excessive number of parameters [5].

3. PROPOSED SYSTEM

Depression is currently a prevalent factor in an upsurge in suicide instances throughout the world. Therefore, a precise evaluation and counselling are essential to alleviate the consequences of depression. The electrical activity of the brain is measured and recorded using an electroencephalogram (EEG). It is capable of producing a reliable evaluation of the degree of depression. Prior investigation established the viability of using deep learning (DL) models with EEG data to diagnose mental disorder. DeprNet is a DL-based convolutional neural network that this research shows be used to categorise EEG data of healthy and depressed patients. A 9 out of 10 on the patient health questionnaire utilised in this instance to indicate how severe the depression is. In this research, the effectiveness of DeprNet in two tests—the record-wise split and the subject-wise split—is given. The findings generated by DeprNet have an accuracy of 0.9937 and an area under the receiver operating characteristic curve of 0.999 whenever data are separated record-wise are taken into consideration. As opposed to that, an accuracy of 0.914 and an AUC of 0.956 are acquired using subject-wise split data. These findings indicate that when CNN is trained on record-wise split data, it overtrains on EEG data from a limited amount of participants. Comparing DeprNet's performance to the other eight baseline models, it is impressive. Additionally, while viewing the final CNN layer, it can be discovered that for depressed people, the right electrodes values are dominant, but for normal subjects, the left electrodes values are significant. The current approach does not categorise depression as positive, negative, or neutral, it takes a lot of time, and there are theoretical limitations as well. The EEG emotion depression dataset was used as input for the proposed method. The input data were obtained from the dataset repository. After that, the data preparation process must be put into action. Dealing with the missing values at this point will help us avoid making the wrong predictions and remove any unnecessary columns from the process. The normalising approaches must then be used. After that, the dataset must be split into test and train groups. Data is separated relied upon ratios. The majority of the information will be available in train. During the test, some of the information will be available. During the training phase, the model is evaluated, and projections are produced during the testing phase. Next, we must put the deep learning classification method into practise. One method to deep learning is the Convolutional Neural Network. Last but not least, the findings of the experiment demonstrate that various performance indicators, including confusion matrix, accuracy, precision, and recall.

The suggested system has a number of benefits, including:

- It works well for a large number of datasets.
- When compared to the current system.
- The experimental outcome is excellent.
- Low time commitment and delivers precise forecast outcomes.

Fig 1: System Architecture

Following section explains several stages that are involved in putting the suggested technique into practice:

Data Selection: The input data was gathered via the dataset repository. EEG depression dataset is employed in this research. The process of choosing data from the EEG emotion dataset to forecast the depressed patient's emotion is known as data selection. This dataset includes EEG brainwave information that was retrieved using our original analytical extraction method. During 3 minutes in each of the three phases, positive, neutral, and negative—two people, a man and a woman, were observed. We utilised a Muse EEG headgear to capture the EEG locations at TP9, AF7, AF8, and TP10 using dry electrodes. The stimuli used to induce the emotions are also collected for six minutes of resting neutral data.

Fig 2: System Flow Diagram

Data Pre-processing: The act of eliminating extraneous information from a dataset is known as data pre-processing. The dataset is transformed through pre-processing data transformation methods into a machine learning-friendly structure. Cleaning dataset in this stage makes it more effective by eliminating faulty and unnecessary data that might affect the dataset's accuracy. Remove missing data: In this operation, Missing data and Nan values are substituted with 0 when they are null. Data was cleared of any errors and missing values as well as duplicates. Encoding data in categories: That categorical data is described as variables having a constrained set of label values. Input and output variables must be numbers for the most of machine learning programs.

Data Splitting: Data availability is a requirement for machine learning to work. Together with the facts necessary for training, test data are also needed to assess the performance of the algorithm and determine how effectively it functions. The input dataset was split into training and testing halves, with the residual 30% used as training data, according to our strategy. The act of breaking available data into 2 pieces,often for cross-validator needs, is known as data splitting. An element of the information is utilised to create a prediction model, also another portion of the data is used to assess the model's effectiveness. Data must be properly separated into training and testing sets before using data mining techniques for analysis. After a data set has been split into a training set and a testing set, a sizable amount of the data is typically utilised for training although a smaller piece is used for testing.

Feature scaling: Feature scaling is crucial for machine learning algorithms that determine the separation between data. A technique for evenly dispersing the independent properties in the data over a defined range is feature scaling. Without feature scaling, a machine learning algorithm would frequently give bigger values the priority above smaller ones, irrespective of the unit of measurement. Scale each characteristic to fall inside a certain range in order to change it. This estimator separately scales and transposes each feature such that it fits inside the training set's predefined range, ranging from zero and one.

Classification: We must use deep learning techniques like Convolutional Neural Network in our procedure. A CNN is a Deep Learning technique capable of receiving an input image, assign various objects and elements value (learnable weights and biases), and be able to differentiate amongst them. With the use of a hierarchical model, the CNN creates a network in the form of a funnel that finally yields a fully connected layer in which all of the neurons are interconnected and the output is analyzed.

Result Generation: The Final Outcome will be produced depending upon the overall classification and projection. This recommended strategy's efficacy is measured using some measures, such as:-

Accuracy refers to the classifier's capacity. Predictor accuracy assesses how well a certain predictor can forecast the value of a characteristic for updated data, and it reliably forecasts the class label.

AC = TP + TN / TP + TN + FP + FN

The ratio of the total number of genuine positives to the total number of true positives and false positives is known as precision. Precision is TP/(TP+FP).

By dividing the total number of true answers by the total number of predicted outcomes, recall is computed. When referring to recall in binary classification, the word "sensitivity" is used. It might be interpreted as the probability that the query would return a relevant document. Recall=TP/(TP+FN)

F measure, which is the weighted harmonic mean of the test's precision and recall, is a unit of measurement a test's accuracy. F-measure = 2TP/2TP+FP+FN.

4. RESULTS

Depression is a mood disorder that is becoming more prevalent. We improved an EEG-based feature classification technique that uses spatial information and is beneficial for the identification of depressed patients are assisted by a face-in-the-crowd task stimulation test that used time information feature extraction, frequency information filtering and spatial information feature selection. Convolutional neural networks and other deep learning algorithms are used to construct the suggested system (CNN). The technique was created using an analysis of the EEG depression dataset to determine if a patient is positive, negative, or neutral. Among the research results that demonstrate the confusion matrix are the accuracy, recall, precision and f1-score.

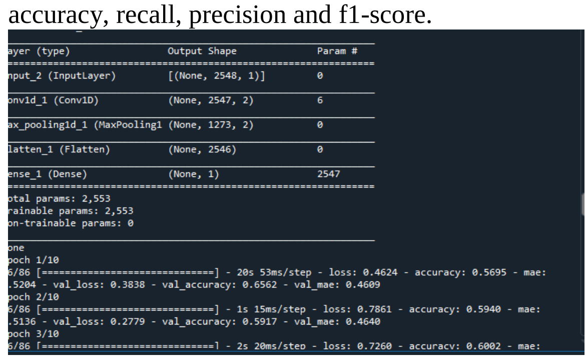

Fig 3: CNN

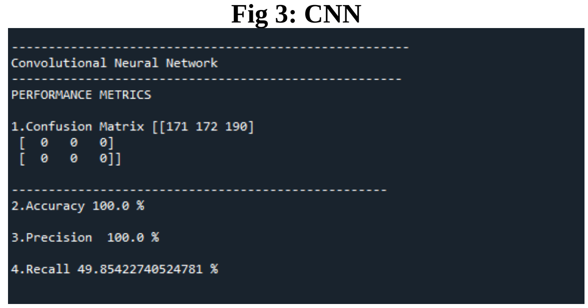

Fig 4: Performance Analysis

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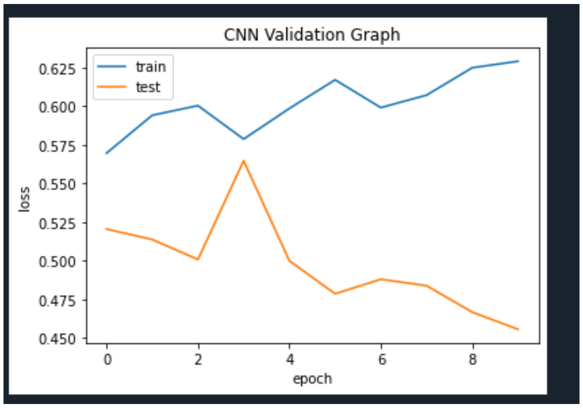

Fig 5: CNN Validation Graph

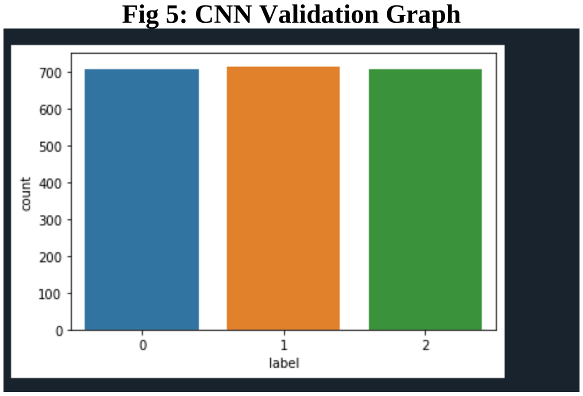

Fig 6: Visualization Graph

5. CONCLUSION

In this research, a deep learning CNN algorithm is implemented. This approach effectively uses DL models to analyse EEG data and show how depression changes the brain's activity. One may assert that the CNN-based DL model called DeprNet, which was suggested in this work, outperforms the other baseline techniques. An increasing number of individuals are being affected by depression, a mental condition. With the use of spatial information, we created a better EEG-based feature classification technique that may identify depressive individuals. With the use of frequency information filtering, spatial information feature selection also time information feature extraction, this method was developed as a face-in-the-crowd task stimulus experiment. Although we should be careful of the dataset limitations, using the classification performance was greatly enhanced, suggesting that it may be possible to increase the spatial differences prior to feature extraction.

6. FUTURE ENHANCEMENT

In order to increase performance, we would like to combine two separate machine learning or deep learning algorithms into a multi-layered model. It would be fascinating to assess how well various unsupervised algorithms do in future work. Additionally, we separately used a number of deep learning as well as machine learning methods. To strengthen the effectiveness of detection, we would like to merge several machine learning as well as deep learning techniques into multi-layered model in the future.

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