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A Deep Convolution Neural Network Framework for Detecting Depression Using EEG

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ABSTRACT

An upsurge in suicide instances around the world is frequently caused by depression. Therefore, a precise diagnosis and treatment are required to lessen the consequences of depression. The electrical activity of the brain is measured and recorded using an electroencephalogram (EEG). It can be used to generate 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. DeprNet is a DL-based convolutional neural network (CNN) that this study suggests be used to classify 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. In this study, the effectiveness of DeprNet in two experiments—the record-wise split and the subject-wise split—is given. When record wise 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 subject-wise split data are used, an accuracy of 0.914 and an 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. Comparing DeprNet's performance to the other eight baseline models, it is impressive. Additionally, it is discovered that the values of the final CNN layer are right electrodes are prominent for depressed subjects, whereas, for normal subjects, the values of left electrodes are prominent.

KEYWORDS:

DeprNet, Convolutional Neural Network (CNN), Electroencephalogram.

1. INTRODUCTION

A physical brain disease known as a mental illness, commonly referred to as a mental health issue, may have an impact on one's thoughts, actions, and mood. Additionally, it causes a loss 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 [1]. Therefore, early diagnosis 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 symptoms of depression

As a result, doctors 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. Furthermore, due to the stigma associated with mental illness, sad patients are less likely to seek treatment. As a result, a sizable proportion of those who are depressed do not receive the optimum treatment and adequate recovery time. Therefore, developing appropriate and effective methods for diagnosing depression is a developing topic of study, and recent advancements in instrument or sensor technology open 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. Because the EEG signal obtained from the parietal lobe of the human brain is associated with cognitive tasks and emotional states [3,] it has been noticed that the majority of cognitive behaviour and psychological activities are examined by EEG [2].

2. EXISTING SYSTEM AND ITS LIMITATIONS

In the existing system there was no proper method to identify the depression detection as we did not have any existing system for this project. We come up with new idea depression detection. Now a day's Depression is a common reason for an increase in suicide cases. 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. To predict the depression we are using Kaggle datasets to implement the depression detection project.

LIMITATION OF PRIMITIVE SYSTEM

1. More Time Delay in finding the cause of depression
2. There is no prevention technique due to late prediction.
3. There is no early prediction of depression and hence it causes suicide for the users.
4. There is no method to identify the depression based on either ML or CNN.

3. PROPOSED SYSTEM AND ITS ADVANTAGES

In this project we took a real time experimented EEG signal data from Kaggle Here I am Specifying the data set links belowhttps://www.kaggle.com/datasets/inancigdem/eeg-data-for-mental-attention-state-detection https://www.kaggle.com/datasets/birdy654/eeg-brainwave-dataset-mental-state.

Whatever the data we took it is present in the form of .mat file we are pre-processing and refining the data algorithm friendly to get a better prediction. After refining the data we are applying KNN and support vector machine algorithms and for the same problem statement we applying CNN and LSTM architectures As well for all these algorithms we are checking their performance individually and finally we are comparing their accuracy in all the models CNN Architecture is giving best result comparatively SVM giving accuracy closed to CNN that's why we are using SVM to predict output for new sample in this project but for real time prediction we can use either CNN or SVM.

ADVANTAGES OF THE PROPOSED SYSTEM

1) By using several modes we can easily detect the depression with more accuracy.

2) In this paper we survey different papers in which one or more algorithms are used for depression detection.

3) Result from using neural networks is very accurate and almost 99 % accurate in identifying the depression.

4. IMPLEMENTATION PHASE

Implementation is the stage where the theoretical design is converted into programmatically manner. In this stage we will divide the application into a number of modules and then coded for deployment. The front end of the application takes Google Collaboratory. Here we are using Python as Programming Language to implement the current application. The application is divided mainly into following 5 modules. They are as follows:

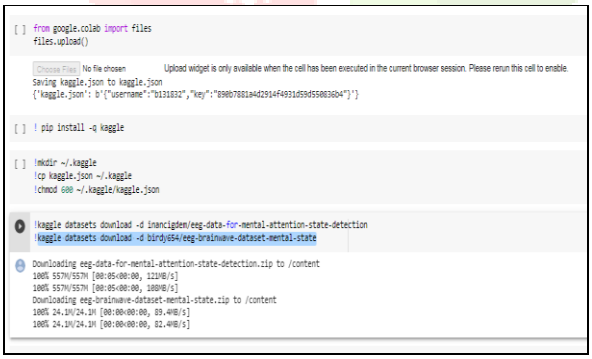
1. Import Necessary Libraries
2. Load Dataset Module
3. Data Pre-Processing
4. Train the Model Using Several Algorithms
5. Find the Performance of ML Algorithms

1) IMPORT LIBRARY MODULE

In this module initially we need to import all the necessary libraries which are required for building the model. Here we try to use all the libraries which are used to convert the data into meaningful manner. Here the data is divided into numerical values which are easily identified by the system,hence we try to import numpy module and for plotting the data in graphs and charts we used matplot library.

2) LOAD DATASET MODULE

In this module the we try to load the dataset which is downloaded or collected from UCI repository. Here we store the dataset names as ‘Heart.csv ‘file and this dataset contains the following information such as :


```
[ ] from google.colab import files
    files.upload()

    Choose Files No file chosen    Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
    Saving kaggle.json to kaggle.json
    {'kaggle.json': b'{"username":"b131832","key":"890b7881a4d2914f4931d59d550836b4"}'}

[ ] ! pip install -q kaggle

[ ] !mkdir ~/.kaggle
    !cp kaggle.json ~/.kaggle
    !chmod 600 ~/.kaggle/kaggle.json

    !kaggle datasets download -d inancigdem/eeg-data-for-mental-attention-state-detection
    !kaggle datasets download -d birdy654/eeg-brainwave-dataset-mental-state

    Downloading eeg-data-for-mental-attention-state-detection.zip to /content
    100% 557M/557M [00:05<00:00, 121MB/s]
    100% 557M/557M [00:05<00:00, 108MB/s]
    Downloading eeg-brainwave-dataset-mental-state.zip to /content
    100% 24.1M/24.1M [00:00<00:00, 89.4MB/s]
    100% 24.1M/24.1M [00:00<00:00, 82.4MB/s]
```

Each and every attribute contains some information which are tested and collected based on individual patient id.

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3) DATA PRE-PROCESSING MODULE

Here in this section we try to pre-process the input dataset and find out if there are any missing values or in-complete data present in the dataset. If there is any such data present in the dataset, the application will ignore those values and load only valid rows which have all the valid inputs.


```
[ ] channels = ['AF3', 'F7', 'F3', 'FC5', 'T7', 'P7', 'O1', 'O2', 'P8', 'T8', 'FC6', 'F4', 'F8', 'AF4']

    channel_idx = [0,1,2,3,4,5,6,7,8,9,10,11,12,13]

[ ] inp_dir='EEG Data/'

    for s in range(1, total_subjects+1):
        data = {}
        data['channels'] = channels
        data['samp_freq'] = samp_freq
        for i, t in enumerate(subject_map[s]):
            trial = {}
            trial_data = loadmat(inp_dir + f'eeg_record{t}.mat')
            eeg = trial_data['o']['data'][0][0][:, 3:17]
            eeg = eeg[:, channel_idx]
            trial['focussed'] = eeg[:mkpt1]
            trial['unfocussed'] = eeg[mkpt1:mkpt2]
            trial['drowsed'] = eeg[mkpt2:mkpt3]
            data[f'trial_{i+1}'] = trial
        with open(f'subject_{s}.pkl', 'wb') as f:
            pickle.dump(data, f, pickle.HIGHEST_PROTOCOL)

[ ] with open('subject_1.pkl', 'rb') as f:
        data = pickle.load(f)

[ ] data
```

4) TRAIN THE MODEL

Here we try to train the current model on given dataset using several ML classification algorithms and then try to find out which algorithms suits best in order to identify and classify the input dataset accurately and efficiently. Here we try to use following algorithms on input dataset such as:

1. Support Vector Machine
2. K-Nearest Neighbors
3. LSTM
4. CNN

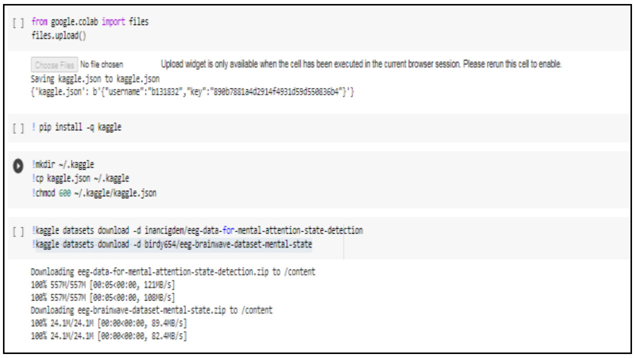
5) PERFORMANCE ANALYSIS MODULE

Here in this module we try to compare each and every classification algorithm on given input dataset and then try to find out which one suits best for finding the accurate results. Finally we will identify the best algorithm which gives accurate results in very less time. Here we can see **CNN** gives more accurate result compared with other Algorithms.

5. EXPERIMENTAL RESULTS

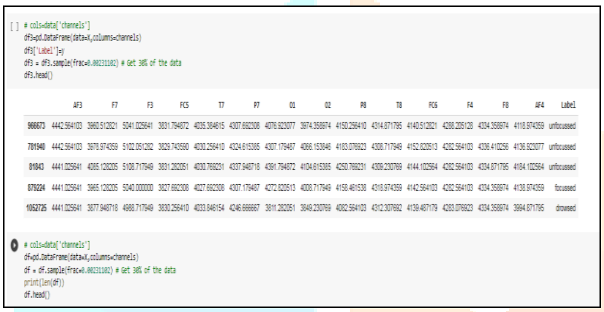
In this section we try to design our current model using Python as programming language and we used Google Collab as working environment for executing the application. Now we can check the performance of our proposed application as follows:

IMPORT LIBRARIES



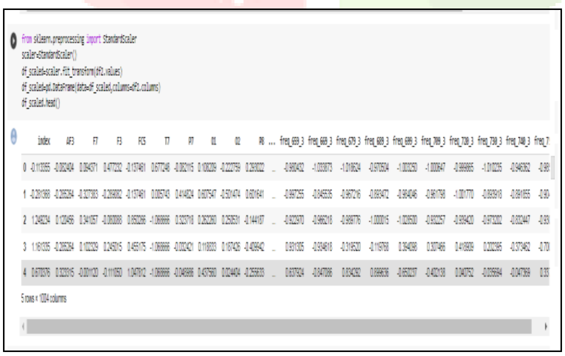
The above window clearly represents the list of several modules used in our application.

PRE-PROCESS THE DATA



From the above window we can see DATA is pre-processed and any incomplete data is removed.

APPLY MODELS



From the above window we can clearly see proposed models are applied.

COMPARISION OF ML-ALGORITHMS

From the above window we can clearly the comparison of several algorithms and we can see CNN has good accuracy.

6. 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 obtained. These findings imply that CNN overtrains on EEG data with a small number of subjects when trained on recordwise split data.

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