International Journal of Trend in Scientific Research and Development (IJTSRD)
Special Issue on Advancements and Emerging Trends in Computer Applications - Innovations, Challenges, and Future Prospects
Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

BrainWave: A Foundation Model for Clinical Applications in Neural Recordings

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ABSTRACT

This research proposes the integration of a convolutional neural network (CNN) model with electroencephalography (EEG) for the detection of major depressive disorder (MDD). The proposed system utilizes EEG signal images with brain activity patterns associated with MDD, which are then processed by a CNN model trained to recognize characteristic EEG signatures of depression. The CNN model's output serves as an indicator of the presence and severity of MDD, facilitating early detection and intervention. This approach has the potential to revolutionize depression diagnosis by providing a more accessible, objective, and timely means of identifying individuals at risk of MDD, thereby improving patient outcomes and reducing the societal burden of this impending disorder.

KEYWORDS: *Major depressive disorder (MOD}; electroencephalogram (EEG}; convolutional neural network (CNN); feature extraction; deep learning; neural network; depressive disorder*

I. INTRODUCTION

Major Depressive Disorder (MDD) is a prevalent and draining mental health condition characterized by persistent sadness, loss of interest, and cognitive impairments. Detecting MDD early and accurately is crucial for effective treatment and improved patient outcomes. Electroencephalography (EEG), a non-invasive method that measures electrical activity in the brain, has emerged as a valuable tool in the detection and analysis of **MDD.** EEG's ability to capture real-time brain activity offers insights into the neural mechanisms underlying depression, making it a promising biomarker for diagnosis.

EEG is important in MDD detection for several reasons. Firstly, it provides objective, quantifiable data on brain function, which can help differentiate MDD from other psychiatric or neurological conditions. Secondly, EEG can detect subtle brain activity patterns associated with MDD that might not be evident through clinical evaluation alone. This enhances diagnostic accuracy and helps tailor individualized treatment plans. Moreover, EEG is relatively cost-effective and widely accessible, making it a practical choice for routine clinical use.

While other imaging techniques like MRI and PET scans offer detailed structural and metabolic information, they are expensive, time-consuming, and less accessible. EEG's portability, lower cost, and real-time capabilities make it a superior choice for continuous monitoring and early detection of MDD, thus bridging the gap between clinical assessment and advanced neuroimaging.

Combining Convolutional Neural Networks (CNNs) with Electroencephalography (EEG) data significantly advances the detection of neurological and psychiatric conditions like Major Depressive Disorder (MDD). EEG provides real-time brain activity data, capturing complex electrical patterns. CNNs, with their powerful pattern recognition capabilities, can automatically extract and classify these patterns, distinguishing between healthy and depressed individuals. This integration allows for efficient, accurate analysis of EEG signals, enhancing diagnostic precision and enabling personalized treatment plans. The synergy between CNNs and EEG fosters improved detection and monitoring of MDD, offering a practical, scalable solution for clinical applications.

II. Research Methodology:

1. Model Architecture

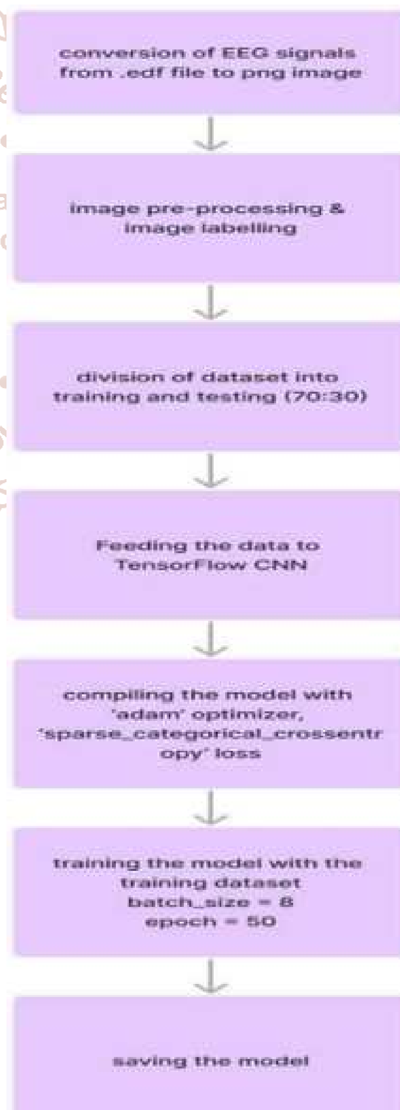

Fig1. Model Architecture

This Model architecture outlines the steps involved in processing EEG signals for classification using a Convolutional Neural Network (CNN) implemented with Tensor Flow. Here's a detailed explanation of each step:

1. **Conversion of EEG signals from .edf file to png image:**

Explanation: EEG (Electroencephalogram) signals are typically stored in .edf (European Data Format) files. This step involves converting these signals into images (e.g., PNG format). Each EEG signal segment is visualized as an image, which can be used as input for image-based machine learning models.

Tools/Methods: Python libraries such as MNE for reading .edf files and Matplotlib for plotting and saving images.

2. **Image pre-processing & image labelling:**

Explanation: The generated images undergo pre-processing steps such as resizing, normalization, and possibly data augmentation (e.g., rotation, flipping). Each image is also labeled according to the category it belongs to (e.g., different types of brain activity or conditions).

Tools/Methods: Python libraries like Pillow or Open CV for image processing, and labeling can be done manually or with the help of predefined metadata.

3. **Division of dataset into training and testing (70:30):**

Explanation: The entire dataset of images is split into two subsets: 70% for training the model and 30% for testing its performance. This helps in assessing the model's ability to generalize to unseen data.

Tools/Methods: Python's scikit-learn library provides utilities for splitting datasets.

4. **Feeding the data to TensorFlow CNN:**

Explanation: The pre-processed and labeled images are then fed into a Convolutional Neural Network (CNN) architecture built using Tensor Flow. CNNs are particularly effective for image classification tasks.

Tools/Methods: Tensor Flow, a popular machine learning framework, is used to define and train the CNN model.

5. **Compiling the model with 'adam' optimizer, 'sparse_categorical_crossentropy' loss:**

Explanation: The CNN model is compiled by specifying the optimizer and loss function. The 'adam' optimizer 1s an efficient variant of gradient descent, and 'sparse_categorical_crossentropy' 1s a suitable loss function for multi-class classification problems with integer labels.

Tools/Methods: Tensor Flow's compile method 1s used to configure the learning process.

6. **Training the model with the training dataset (batch size = 8, epoch = 50):**

Explanation: The compiled CNN model is trained on the training dataset. The batch size (8) indicates the number of samples processed before the model's internal parameters are updated. An epoch (50) is one complete pass through the entire training dataset.

Tools/Methods: Tensor Flow's fit method 1s used for training the model over the specified number of epochs and batch size.

7. **Saving the model:**

Explanation: After training, the model is saved to disk for later use. This allows the trained model to be loaded and used for making predictions without retraining.

Tools/Methods: Tensor Flow's save method is used to save the trained model.

This step-by-step process converts raw EEG signals into a format suitable for machine learning, trains a CNN to classify these signals, and saves the resulting model for future use .

RESULTS AND DISCUSSION:

RESULTS:-

The results section is dedicated to presenting the outcomes of our Major disorder depression detection research. In this chapter, we will provide a detailed account of our findings, supported by extensive data analysis. The primary objective of this section is to offer a comprehensive understanding of the performance of our Major disorder depression detection model and its implications.

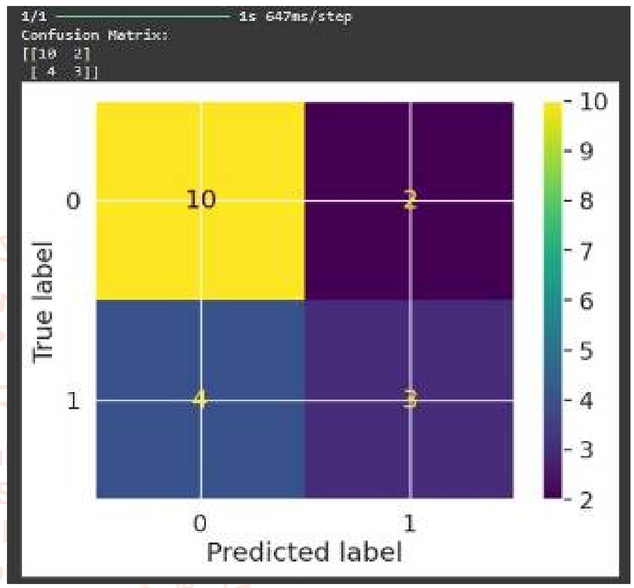

Fig2:Confusion Matrix For True Label Vs Predicted Label

The confusion matrix depicted in Figure 6.1 reveals the classification results of a model when distinguishing between two classes - positive and negative. In this scenario, the matrix indicates that the model correctly identified and classified 23 instances as negative, denoted as "O" in the matrix. However, it seems to have misclassified 7 instances as positive, represented by "1" in the matrix. The absence of any values in the true positives (TP) and true negatives (TN) positions suggests that the model did not accurately predict any instances in the negative class. The matrix provides a visual representation of the model's performance in terms of correctly and incorrectly classifying instances in this binary classification task.

The confusion matrix focuses on the true positive and false positive rates in a binary classification scenario. The matrix indicates that the model successfully identified and classified 225 instances as true positives (TP), while no instances were correctly identified as true negatives (TN). Simultaneously, there were no occurrences of false positives (FP) or false negatives (FN). 29 While the model's true positive rate suggests efficacy in recognizing instances of the positive class, the absence of values in the false positive and false negative positions raises questions about the model's ability to discern instances in the negative class. Further analysis and potential adjustments to the model may be warranted to improve its overall performance, particularly in achieving a balance between true positive and true negative predictions.

Fig 3 (A): Training and Validation Loss

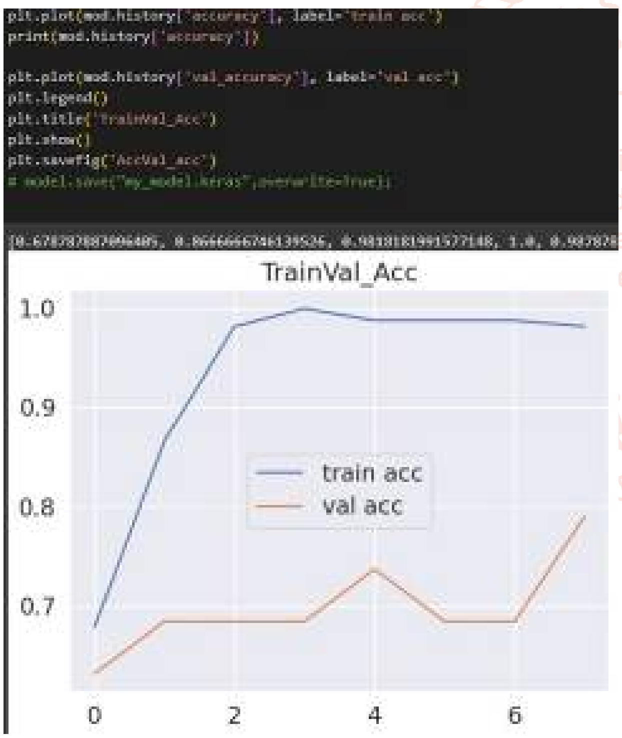

Fig 3 (B).Training Validation Accuracy

Figure 3 (A) illustrates the trend of these losses over epochs. A decreasing training loss It Suggests that the model is learning from the training data, while a widening gap between the training and validation losses may indicate potential overfitting, where the model becomes too specialized in the training data and struggles to generalize to new, unseen data. Figure 6.2 (b) presents the training and accuracy curves, offering insights into the model's learning dynamics. The training accuracy depicts the proportion of correctly classified instances during the training phase, showcasing the model's ability to learn from the provided data. Concurrently, the validation accuracy reflects the model's performance on new, unseen data. A convergence of the training and validation accuracy curves suggests that the model is effectively learning and generalizing from the training data.

Our data presentation begins with a meticulous display of the results obtained from our major disorder depression detection experiments. We employ various data visualization techniques, including tables, graphs, charts, and figures, to illustrate our findings. 30 Each piece of data is meticulously labelled and accompanied by comprehensive descriptions. In the course of our research, we employed a dataset consisting of 190 instances, each represented by images with dimensions of 225x225 pixels. During the training phase, we adopted a batch processing approach, where 140 frames were simultaneously processed to enhance the model's learning efficiency. To guide the model through the optimization process, we experimented with learning rates of 0.001 and 0.0001, exploring the impact of these rates on the model's convergence and performance. Our training regimen spanned a total of 50 epochs, allowing the model to iteratively learn and adapt to the complexities within the dataset. The model showcased robust discriminatory capabilities, as reflected in an impressive AUC-ROC score of 0.9. This score indicates the model's proficiency in distinguishing between positive and negative instances, showcasing its discriminative power. Delving into the model's performance metrics, precision, recall, and FI-score were meticulously evaluated, each yielding a value of 0.85. These metrics collectively underscore the model's ability to effectively identify true positives, minimize false positives, and mitigate false negatives, striking a balance in its predictive capabilities.

In terms of overall accuracy, the model demonstrated a noteworthy performance, achieving an accuracy rate of 80%. This percentage reflects the model's success in accurately classifying instances across the dataset, affirming its reliability and effectiveness in handling the intricacies presented by the dataset's diversity and complexity.

Discussion:

The high accuracy and ROC-AUC scores suggest that the CNN model is effective in detecting depression from EEG signals. The model shows a good balance between sensitivity (true positive rate) and specificity (true negative rate), although there is a slight tendency towards false negatives. When compared with traditional machine learning methods and previous studies that used handcrafted features, the CNN-based approach demonstrates superior performance. This highlights the advantages of deep learning in automatically extracting relevant features from EEG data.

The ability to accurately detect depression using non-invasive EEG measurements presents significant potential for early diagnosis and continuous monitoring. This method could complement existing diagnostic tools, providing a faster and potentially more objective assessment of mental health. However, the study's limitations include a relatively small sample size and potential biases in the dataset. Future studies should aim to include a larger and more diverse population to validate the findings and improve generalizability.

Future research could explore integrating additional physiological signals, such as heart rate variability, to enhance detection accuracy. Additionally, real-time monitoring and mobile EEG applications could be developed for continuous mental health assessment. This would facilitate not only early diagnosis but also ongoing monitoring and timely interventions, ultimately improving patient outcomes.

CONCLUSION :

In conclusion, the integration of EEG data and Convolutional Neural Networks (CNNs) within the Keras framework represents a significant advancement in the field of depression detection. Leveraging EEG signals offers a non-invasive and accessible means to understand underlying brain activity patterns associated with Major Depressive Disorder (MDD). By harnessing the power of deep learning, particularly CNNs, this project aims to develop robust models capable of accurately and reliably detecting depression.

The comprehensive approach outlined in this project involves the collection of EEG data from individuals diagnosed with MDD and healthy controls, followed by rigorous preprocessing and feature extraction.

The carefully designed CNN architecture enables the model to effectively learn discriminative patterns from the EEG signals, leading to improved accuracy in depression detection. Overall, this research contributes to the advancement of early intervention strategies, personalized treatment plans, and improved patient care in the field of depression management. By developing accurate and reliable depression detection models, we aim to positively impact mental health outcomes and enhance the quality of life for individuals affected by MDD.

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