Fusion Based Depression Detection through Artificial Intelligence using Electroencephalogram (EEG)

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Abstract

Depression is one of the common psychological disorders that affects many people all over the world. The primary typical behavior of depression is persistent low mood, and it is one of the main reasons for disability worldwide. Due to the lack of awareness, treatment, and social stigma, it is leading to suicide and self-harm. It is necessary to identify the depression at a very initial stage to overcome further complications that may lead to suicide. In recent years, certain studies have been done on identifying depression through Machine Learning and Deep Learning techniques. Electroencephalogram (EEG) can be used to detect depression since it is easy to record and non-invasive. The current paper focuses on developing an algorithm that will use the brain signals received through EEG and predict the person as Healthy or with Major Depressive Disorder (MDD) with the help of CNN through an asymmetry matrix, which achieved an accuracy of 89.5%, and it outperformed the previous traditional models. The current study shows that depression detection through EEG is one of the efficient techniques for detecting depression at its early stages.

Keywords: Clinical Depression; Artificial Intelligence; Machine Learning; Pattern Recognition; Mathematical Fusion; Convolutional Neural Network; Electroencephalogram (EEG); Depression; EEG Asymmetry; European Data Format; EEG Visualization; Fusion Based

1. Introduction

According to the World Health Organization (WHO) [1], depression is one of the leading causes of global disability worldwide. 5% of adults suffer from depression worldwide, and it is characterized by persistent sadness or loneliness and a lack of pleasure. This disorder can affect sleep and appetite, affecting day-to-day activities in the long term. Depression often results from complex interactions among social, psychological, and biological factors, and it is estimated that 75% of those affected do not receive any medical treatment. 90% of suicide cases are linked to psychiatric issues or depression, which urges for effective depression treatment. Recent advancements in Artificial Intelligence have shown that the detection of depression with EEG brain signals plays a pivotal role in its identification through deep learning techniques.

Human cerebral activity is used to understand human negative emotions and depression, as discussed in [2]. Current practical methods are subjective and depend on the psychiatrist's experience to diagnose and treat depression. EEG is a process of recording human brain activity where sensors are attached to the scalp to read electrical signals from the brain. EEG helps capture emotions and biological signals, and it depicts the different states of the brain with a range of frequencies. EEG is a cost-effective, safe, and non-invasive method to study the brain and its effects on depression. Studies have shown that there is an association between mental disorders and brain function using EEG data [3].

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The current study proposes a novel approach to detect depression using EEG Signals through CNN. Data preprocessing is performed to convert the EEG signals to an image, which is further fed to the fully connected Conv2D. Asymmetry of the Brain and asymmetry matrix differentiates between different channels. The CNN model is a binary classification model classified as Major Depressive Disorder (MDD) and Healthy Controls (HC).

2. Related Work

In recent years, extensive research has been conducted on the application of Artificial Intelligence in mental health. However, there is a notable scarcity of studies focusing on depression-related brain activity with AI. The findings presented in [4] show a correlation between the prefrontal cortex and depression. Studies also show asymmetries in the EEG of depressed individuals over the frontal cortex, showing significant distinctions between depressed and healthy subjects. Various classification techniques, including machine learning and deep learning, have been used to identify depression using EEG signals. In [5], the Fast Fourier Transform has been used for the feature extraction of EEG, but there is a drawback: It uses only frequency information and ignores the time domain details. This has been overcome in [6], which combines both frequency and time domain information, which boosts the final accuracy of prediction.

In the research detailed in [7], EEG signals were examined using a 13-layer convolutional neural network, achieving an accuracy of 93.5%. Furthermore, accuracy reached 96% when scalp electrodes were positioned over the left and right hemispheres. Another study [8] focused on creating a deep learning framework with eight EEG frequency bands for Major Depressive Disorder (MDD) detection. The extraction of images from EEG signals and their subsequent input into a convolutional neural network with a combined CNN-LSTM model resulted in an accuracy of 99.24%. In the study outlined in [9], a Support Vector Machine (SVM) was employed to identify and detect depression. By creating a higher dimensional input space and constructing an optimal separating hyperplane, SVM overcomes the challenges posed by high dimensionality, proving efficient for small sample sizes and nonlinear data.

The study in [21] achieved an accuracy of 97% with 128-channel EEG data, and CNN was used with 25 epochs for training the model. Classes were divided into Major Depressive Disorder and Healthy Controls, and for the classification, they used machine learning models like XGBoost, Random Forest, and 1D CNN Model. [22] proposes a study to detect depression from 29 healthy subjects and 24 patients with severe depression. The study achieved an accuracy of 90.98% accuracy on the dataset for depression detection with the help of the EEGNet CNN Model, which had four blocks, namely convolution, depth-wise convolution, separable convolution, and classification. EEG-based Major Depressive disorder and bipolar disorder detection methods are discussed in [23] with the help of Neural Networks. They conclude that neural network-based methods exhibit predictive solid performance but fall short in providing adequate model explainability crucial for quantitative research. This limitation hinders the community from advancing reproducible and deterministic protocols and achieving clinically valuable outcomes.

In the article [24], the author proposes an approach to detecting depression using EEG signals in multi-brain regions. They used frequency domain feature power spectral density (PSD) and nonlinear feature Lempel–Ziv complexity (LZC) to analyse the EEG signals. They also studied the opened and eyes closed states and their effect on different brain regions for detecting Major Depressive Disorder. Depression detection in the temporal region achieved an accuracy of 87.4%, and in the brain, region achieved an accuracy of 92.4%. The author [25] proposes an automated depression detection using sequence learning and deep representation with the help of EEG signals. They propose a deep hybrid model using long-short-term memory (LSTM) and convolutional neural network (CNN) architectures to detect depression. EEG signals from the left and right hemispheres of the brain are obtained, and an accuracy of 99.12% and 97.66% classification accuracies are achieved with the help of LSTM and CNN.

[26] focuses on depression detection based on geometrical features extracted from the SODP shape of EEG signals and Binary PSO. The effectiveness of the suggested framework was assessed using bipolar EEG signals obtained from 22 individuals categorized as normal and 22 individuals diagnosed with depression. The study achieved a classification accuracy of 98.79% with a KNN classifier in a ten-fold cross-validation approach. [27] discusses the implementation of Depression Detection Using

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Dynamic Convolution and Feature Adaptation. The study achieved an accuracy of 86.85% in detecting subject independent MDD using the multimodal open mental disorder analysis (MODMA) dataset.

Current research introduces an innovative method for depression detection using EEG via Convolutional Neural Network (CNN). The EEG signals undergo data preprocessing to transform them into images, subsequently inputted into the Fully Connected Conv2D. Brain asymmetry and the asymmetry matrix are used for distinguishing between various channels. The CNN model operates as a binary classification system, categorizing individuals into Healthy Controls (HC) or Major Depressive Disorder (MDD). This approach proves effective for identifying depression at its early stages.

2. Data Analysis

A. Dataset

Our research used the publicly available dataset documented in [10], comprising 34 patients diagnosed with Major Depressive Disorder (MDD) and 30 Healthy Controls. The dataset, formatted in EDF, has 19 channels, providing details from the frontal, parietal, occipital, and temporal regions. It has three distinct states—closed eyes, open eyes, and visual stimulus—operating at 256 samples per second sampling rate. In this current study, our analysis focuses on the data recorded during periods of both closed and open eyes.

B. Data Processing

As the dataset is presented in EDF format, a necessary step involves converting it to CSV for subsequent processing. The Min-Max Normalization technique is applied to ensure uniform amplitude across all channels. To mitigate noise stemming from eye blinking and muscle movement, Independent Component Analysis (ICA) is employed. Data segmentation is carried out to increase the number of samples, and the resultant intermediate files are stored in CSV format for further data processing. Figure 1 illustrates the EEG data in its raw form and the second figure after applying Independent Component Analysis.

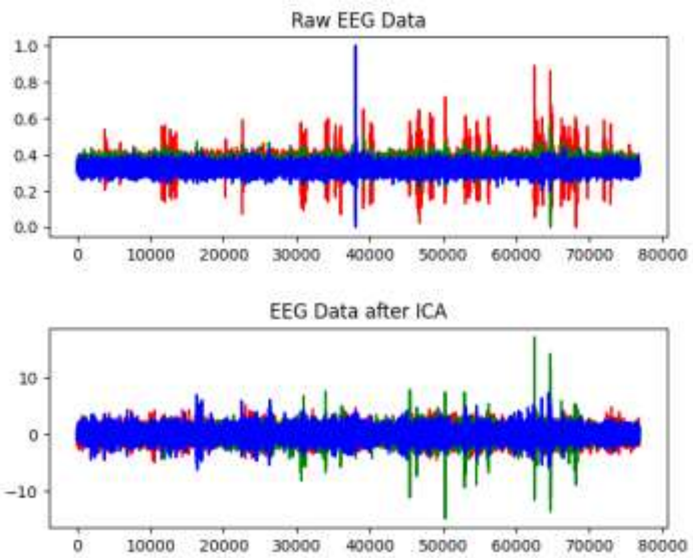

Figure 1: Raw EEG Signals and data after ICA

C. Brain Asymmetry Score

The Asymmetry Score is calculated with the help of the EEG signal power of each channel. Asymmetry images of each band are created by determining the relative powers of alpha (8-13 Hz). Welch's periodogram is used to calculate the EEG signal's power spectrum. Window length is set two times the inverse of the lower frequency of interest, and power spectral density S is calculated using this method. Simpson's approach is used to calculate frequency band power spectral density. The relative power of each channel is calculated using equations (1) and (2), and the output is saved as

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CSV for further consumption. (1) is the relative power of channel one, and (2) is for channel 2 with f1=8Hz and f2=13Hz.

$$R_{p_{ch1}} = \frac{\sum_{f=f1}^{f2} S_{ch1}}{\sum_{f=0.5Hz}^{30\,Hz} S_{ch1}} \quad (1)$$

$$R_{p_{ch2}} = \frac{\sum_{f=f1}^{f2} S_{ch2}}{\sum_{f=0.5Hz}^{30\,Hz} S_{ch2}} \quad (2)$$

The difference between the relative powers of ch1 and ch2 is calculated with the help of equation (3). Parameter A(ch1, ch2) ranges between -1 to +1 and is calculated as the difference between the relative power values of ch1 and ch2. A positive value means a higher relative power and a negative value means a lower relative power.

$$A(ch1, ch2) = \frac{R_{p_{ch1}} - R_{p_{ch2}}}{R_{p_{ch1}} + R_{p_{ch2}}} \quad (3)$$

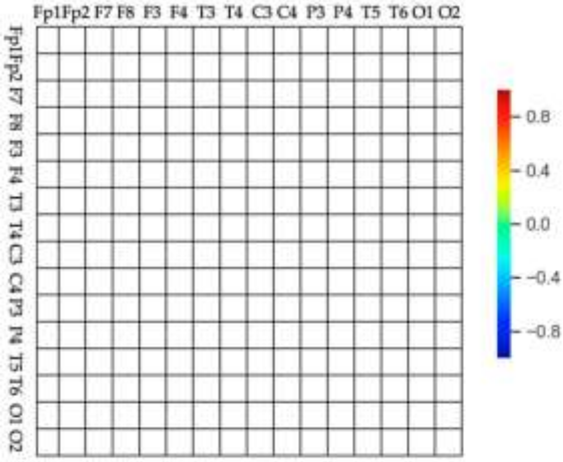

Figure 2: Representation of frames for Brain Symmetry Image, rows and columns corresponds to 16 channels, and every cell corresponds to the value of $A(ch1, ch2)$

D. Convolutional Neural Network

CNN finds widespread applications, with its primary use in image recognition and classification. As a feedforward neural network, it comprehends features through kernel optimization. It operates as a fully connected network, wherein each neuron establishes connections with all neurons in the subsequent layer. Unlike some other image classification algorithms, CNN requires minimal pre-processing. Comprising three layers—input, hidden, and output layer—CNN executes convolutions within the neural network, with the commonly employed ReLU as the activation function. Figure 3 illustrates CNN's standard architecture.

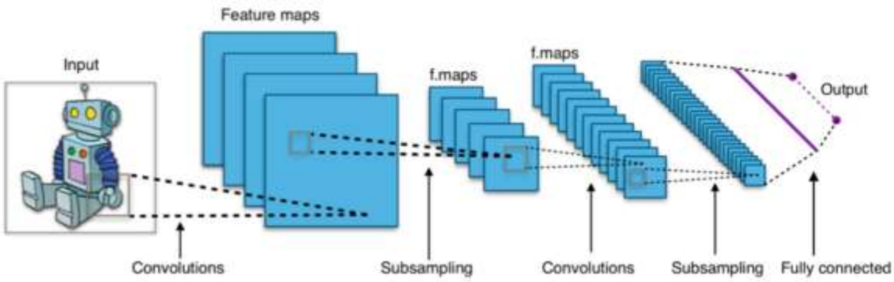

Figure 3: CNN Architecture

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3. Proposed Methodology

This research uses the openly accessible dataset [10] and introduces a Convolutional Neural Network (CNN) methodology to classify depressed and non-depressed categories. The dataset contains 34 individuals diagnosed with Major Depressive Disorder and 30 Healthy Controls. The framework for depression detection from EEG files is illustrated in Figure 4.

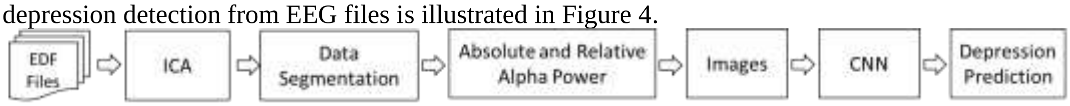


Figure 4: Depression Detection Framework

The information is obtained in European Data Format (EDF), housing both Major Depressive Disorder (MDD) and Healthy Control (HC) data. The data processing is done through Independent Component Analysis (ICA) to convert multivariate signals into additive subcomponents. For each EEG band, an asymmetry image is generated, discerning the relative powers of each alpha. Intermediate files are saved as CSV for training the model. Absolute and Relative Alpha Power values are transformed into matrix images in JPG format. These images are categorized and appropriately labeled as depressed and non-depressed for the model training process.

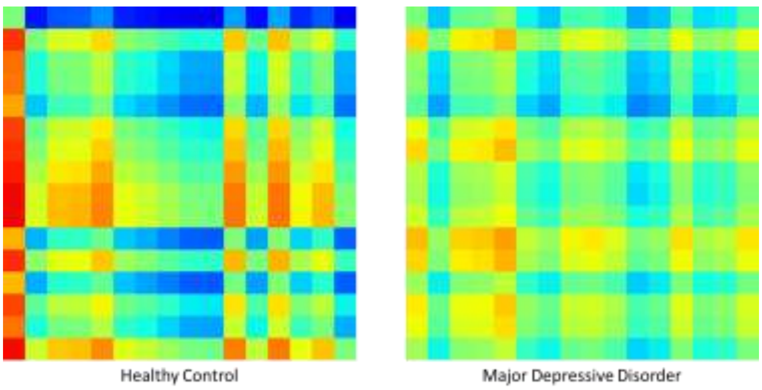
A. Convolutional Layer and Feature Maps

The fundamental functionality of a Convolutional Neural Network centers around the Convolutional Operation, generating Feature Maps through multiple convolutional filters to separate features within the input image. The convolution operation results from the dot product of the image and filter, and it can be mathematically represented as in equation (4).

$$f_m = b_m + \sum_n (X_n \otimes K_{nm}) \tag{4}$$

Where f_m is the m-th feature map, b_m is the m-th bias function and X_n is the n-th input. K_{nm} is the convolutional kernel connecting n-th input with m-th output. $\otimes$ represents the convolution operation. Feature maps are passed through the ReLU activation function to generate output layer y_m as in (5).

$$y_m = \max(0, f_m) \tag{5}$$



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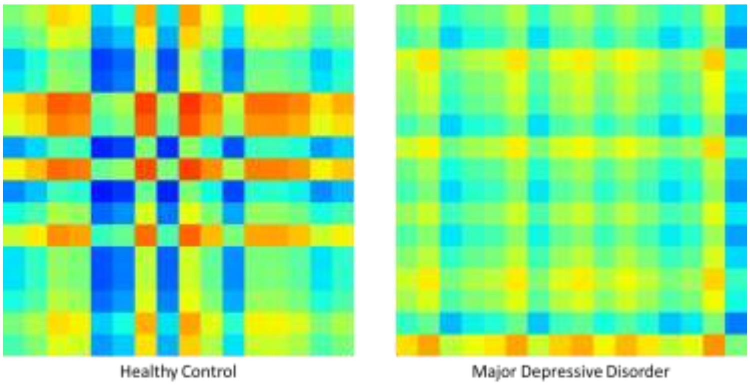

Figure 5: Matrix Depiction for Healthy Control and Major Depressive Disorder

Figure 5 depicts matrix images corresponding to Major Depressive Disorder and Healthy Controls. It is beneficial to segregate the HC and MDD through a visualization chart before building the model. These matrices are derived post Independent Component Analysis, followed by Segmentation involving Absolute and Relative Alpha Power. Subsequently, these images are inputted into the 2D Convolutional Neural Network. An asymmetric image matrix is formulated based on the relative power of the alpha wave, where vivid red and blue hues indicate heightened brain activity. In contrast, yellow and light blue signify lower relative power.

Images exhibiting increased relative power denote a healthy control, while those displaying lower relative power signify a patient with Major Depressive Disorder. A vibrant display of red and blue colors indicates an active brain in a healthy individual, while channels with comparable relative powers are represented by yellow and green. Depressed patients exhibit reduced frontal cortical activity. The Convolutional Neural Network (CNN) is used to pinpoint pertinent features by minimizing errors, focusing on low-level features in the initial layers, and progressively seeking high-level abstraction features in the final layers. The ultimate output layer uses a Sigmoid Function for binary classification into depressed or non-depressed categories. A sigmoid function used is in equation (6).

$$f(x) = \frac{1}{1+ e^{-x}} \quad (6)$$

From the equation (6), we get the calculated values between 0 and 1. If the layer's output is less than 0.5, it will be classified as a healthy patient; if it is more significant than 0.5, it will be classified as a depressed patient. Figure 6 depicts Convolution with 1 Filter, and the reason for visualizing a feature map for a specific input image is to gain an understanding of what features CNN detects.

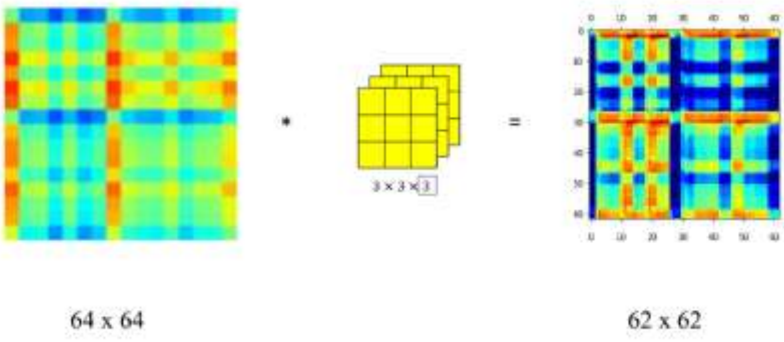

Figure 6: Convolution with 1 filter

B. Classification of Major Depressive Disorder and Healthy Controls

Feature Maps are used in both the input and output layers. Figure 7 below illustrates the visualization of the feature map, providing an in-depth visualization of the features influencing predictions. The below figure helps to deduce and showcase, with the help of a heatmap, the features through visualization.

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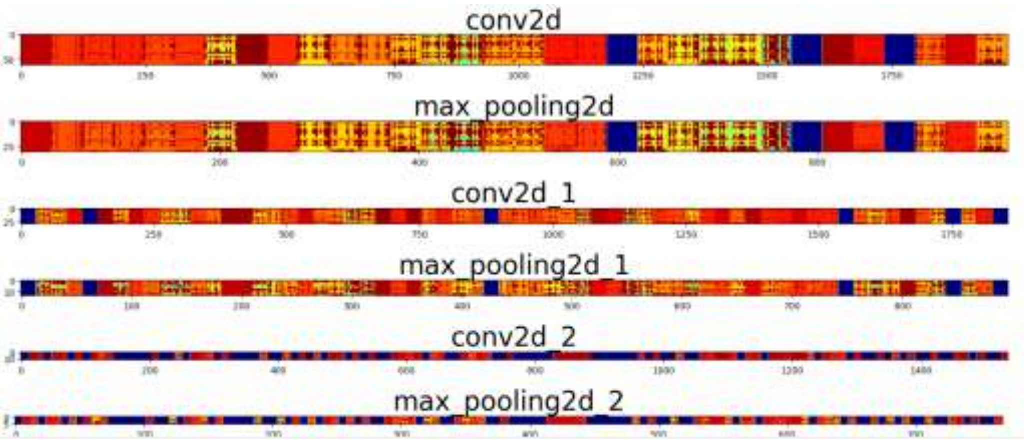

Figure 7: Visualization of Feature Map

A 3D filter is applied to a 3D image, utilizing 32 filters that yield outputs of size 62x62x3, with each channel treated independently. Max pooling is then applied to the spatial data, facilitating the down sampling of input along its spatial dimensions by selecting the highest value within an input window of a specified pool size. The window undergoes shifts by strides over each dimension. This processed information passes through a ReLu activation function in the Conv2D Layer and a sigmoid activation function in the final output layer. The inclusion of Dropout with the Adam optimizer ultimately leads to the classification of depressed and non-depressed cases.

4. Results and Discussions

Google Colab is employed to conduct the experiments due to the Convolutional Neural Network (CNN) GPU requirements. The CNN framework consists of three layers, including Conv2D, a pooling layer, and a fully connected layer. The training process involves utilizing 75% of the data for training and validating the model on the remaining 25% of the test dataset. The model summary is illustrated in both Figure 8 and Figure 9.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 62, 62, 32)        896

 max_pooling2d (MaxPooling2  (None, 31, 31, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 29, 29, 64)        18496

 max_pooling2d_1 (MaxPoolin  (None, 14, 14, 64)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 12, 12, 128)       73856

 max_pooling2d_2 (MaxPoolin  (None, 6, 6, 128)         0
 g2D)

 flatten (Flatten)           (None, 4608)              0

 dense (Dense)               (None, 256)               1179904

 dropout (Dropout)           (None, 256)               0

 dense_1 (Dense)             (None, 1)                 257

=================================================================
Total params: 1273409 (4.86 MB)
Trainable params: 1273409 (4.86 MB)
Non-trainable params: 0 (0.00 Byte)
```

Figure 8: Model Architecture

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The Convolutional Neural Network scans the image within a small window, moving horizontally and vertically to identify features. The neural network separates the critical features within each window throughout this process. The architecture consists of three layers: a 2D Convolutional layer, a pooling layer, and a fully connected layer. Within convolutional networks, the initial layers are designed to identify low-level features, while the subsequent layers focus on extracting higher-level and more abstract information. Weights and activation functions across various feature maps are used to recognize depression, and as the network goes deeper, it helps to capture as many combinations as possible for features.

The model undergoes training for 30 epochs, reaching a point of stability where both accuracy and loss metrics are stabilized. The achieved Training Accuracy stands at 98.5%, with a Validation Accuracy of 89.5% on the test dataset, surpassing the previous model's performance with a similar approach. Notably, the model's scalability is highlighted by converting EEG signals into an image matrix, facilitating real-time implementation for depression detection using EEG signals.

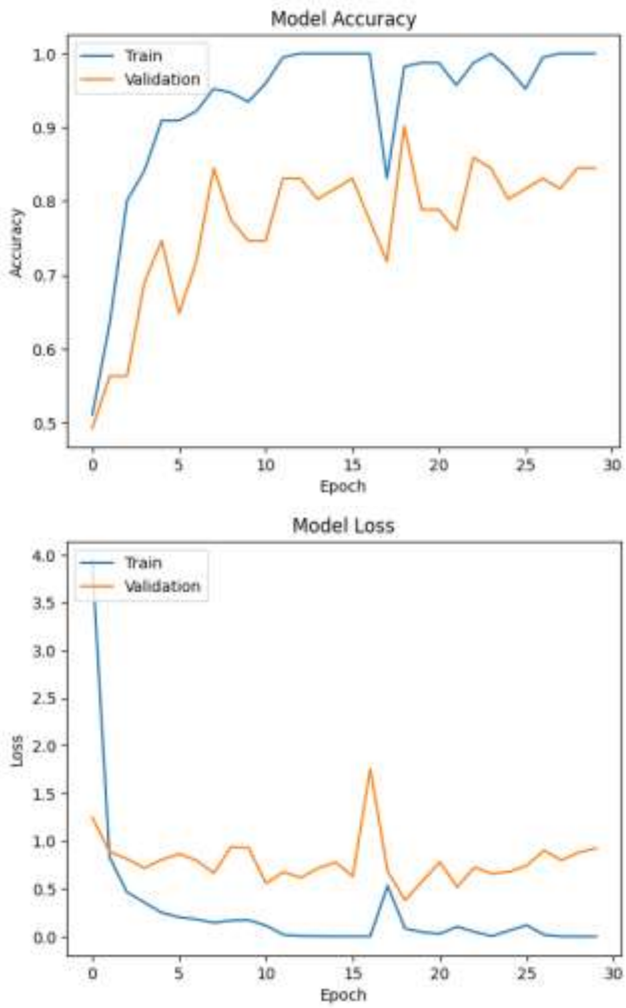

Figure 9: Model Accuracy and Loss

If the dataset is unbalanced, accuracy might not be an acceptable metric (both negative and positive classes have different numbers of data instances). The following metrics are used for validating the model.

Precision: Proportion of anticipated positives that are positive. The precision model is shown in Equation (7). A good classifier's precision should preferably be 1 (high).

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$$Precision = TP/(TP+FP) \quad (7)$$

Recall: The fraction of true positives successfully identified. The recall equation is shown in Equation (8), where recall on an excellent classifier should ideally be 1 (high).

$$\text{Recall} = TP/(TP+F\text{N}) \quad (8)$$

F1 score: The harmonic mean of recall and precision. The F1 Score equation is shown in Equation (9). When precision and recall are both 1, the F1 Score is 1. Only when precision and recall are both strong can the F1 score rise.

$$F1\ Score = 2*Precision*Recall/(Precision+Recall) \quad (9)$$

5. Conclusion

The identification of depression holds significant importance in preserving individuals' well-being, preventing potential suicide, and mitigating self-harm. Early diagnosis and detection of depression are crucial, and leveraging Artificial Intelligence proves beneficial. The present study highlights the effectiveness of utilizing image matrices in depression detection through CNN, showcasing a cost-effective and real-time approach. This method helps to diagnose and report for further treatment. The model showcased an accuracy of 89.5% on the dataset, which outperformed similar previous approaches. Future research could involve optimizing the model with additional datasets and exploring a multi-modal approach by incorporating EEG, facial, and vocal features for more accurate depression detection.

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