Clinical depression detection with EEG signals

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Contents

Introduction

- Depression is a mood disorder that causes a persistent feeling of sadness and loss of interest.
- It is difficult to diagnose and can also be misdiagnosed for other disorders.
- So a reliable system is necessary
- Electroencephalography (EEG) is an efficient method which helps to acquire brain signals corresponds to various states from the scalp surface area.
- Various studies involving EEG based depression diagnosis using deep learning is of great interest.
- Due to its broad variety of capabilities, including feature extraction based on self-learned data and pre-processing, deep learning is frequently employed in medical diagnostics.

Objective

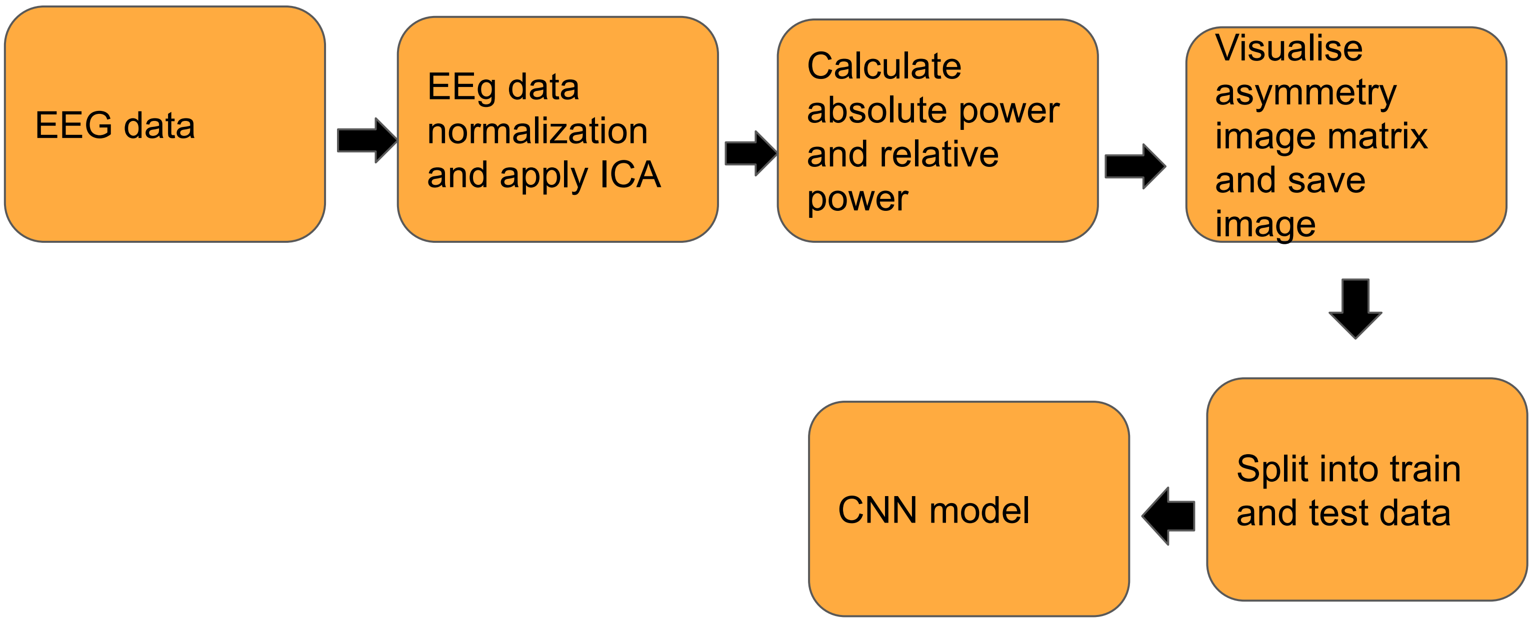
- Brain asymmetry is a promising biomarker for depression detection.
- This study proposes a deep-asymmetry method that converts asymmetry of the EEG signals into a matrix type image and then feeds it into the convolutional neural network
- The cnn model will classify it into healthy and depression patients.

Dataset

- EEG signals of 34 depression patients and 30 healthy controls of age group between 12 to 77 years were gathered
- EEG signals are in .edf format
- The EEG dataset consisted of three types of data: eyes closed (EC), eyes opened (EO), and TASK

Link

BLOCK DIAGRAM



METHODOLOGY

- Step 1: Convert edf file to csv file and read the csv file
- Step 2: Perform MinMax Normalization
- Step 3: Perform ICA for removing noise and store the values in another csv file
- Step 4: Perform data segmentation such that each file has 37925 samples
- Step 5: Calculate power spectral density using welch periodogram
- Step 6: Calculate absolute power for alpha frequency range (alpha frequency range is frequency between 8Hz and 13Hz) using Simpson's method

METHODOLOGY

- Step 7: Calculate total power using Simpson's method
- Step 8: Calculate relative power by dividing absolute power by total power and store it in another csv file

$$\mathrm{Rp_{ch\,1}} = \sum_{f=f_1}^{f2} S_{ch1} \Big/ \sum_{f=0.5\ \mathrm{Hz}}^{30\ \mathrm{Hz}} S_{ch1}$$

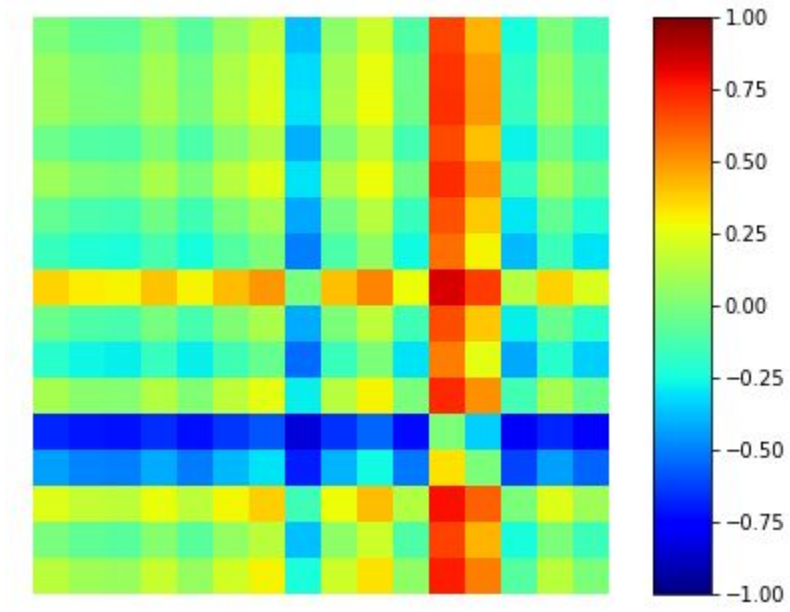
$$\mathrm{Rp_{ch\,2}} = \sum_{f=f_1}^{f2} S_{ch2} \Big/ \sum_{f=0.5\ \mathrm{Hz}}^{30\ \mathrm{Hz}} S_{ch2}$$

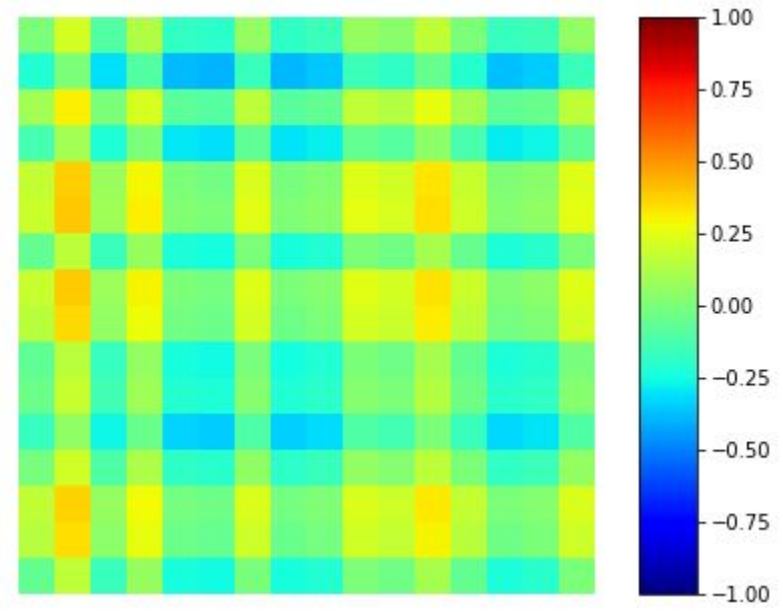
- Step 9: Calculate A(ch1, ch2) by formula to convert values from range -1 to 1 (Rpch1 - relative power of channel 1)

$$\mathrm{A\,(ch\,1, ch\,2)} = \frac{\mathrm{Rp_{ch\,1}} - \mathrm{Rp_{ch\,2}}}{\mathrm{Rp_{ch\,1}} + \mathrm{Rp_{ch\,2}}}$$

METHODOLOGY

Step 10: Plot colormap and save the image





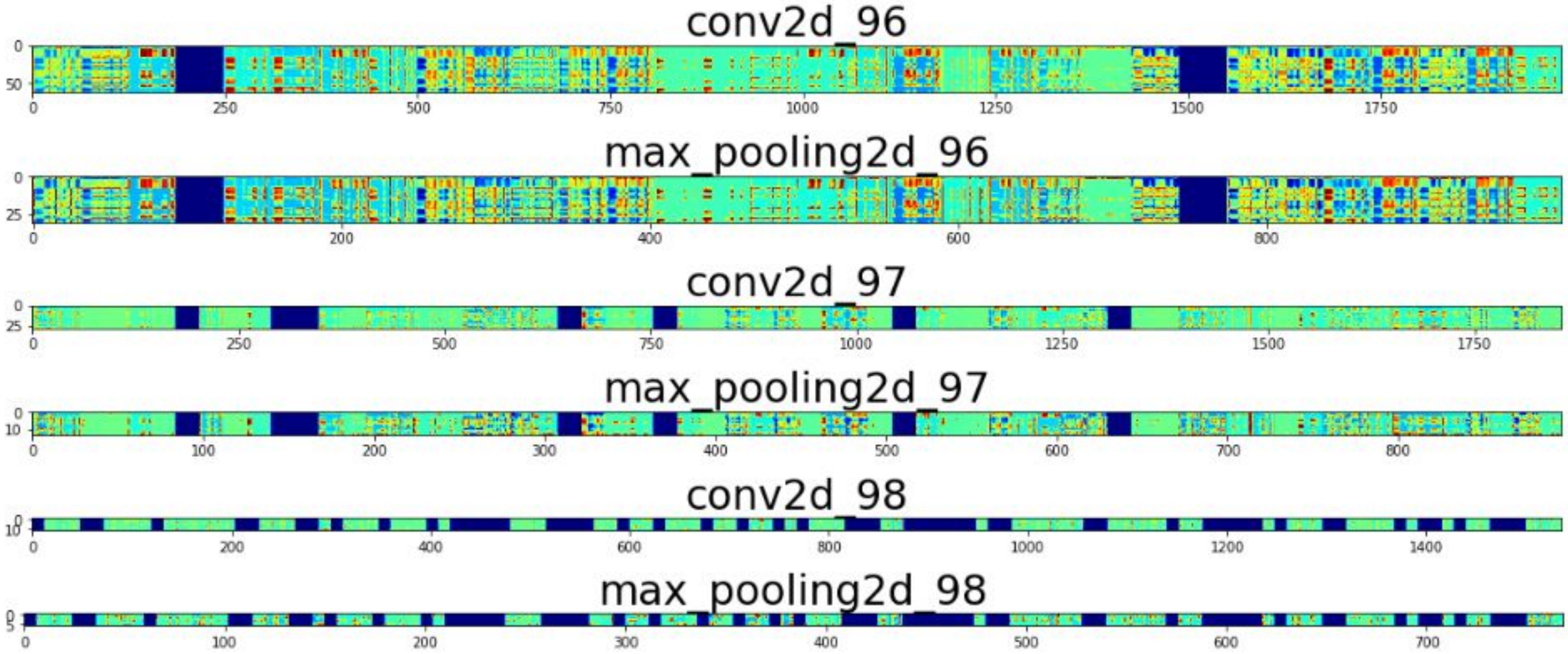
CNN

- The binary cross-entropy loss function and 100 epochs were used .The training was performed using Adam optimizer and learning rate was set to 0.0001

Layer (type)	Output Shape	Param #
conv2d_96 (Conv2D)	(None, 62, 62, 32)	896
max_pooling2d_96 (MaxPooling2D)	(None, 31, 31, 32)	0
conv2d_97 (Conv2D)	(None, 29, 29, 64)	18496
max_pooling2d_97 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_98 (Conv2D)	(None, 12, 12, 128)	73856
max_pooling2d_98 (MaxPooling2D)	(None, 6, 6, 128)	0
flatten_32 (Flatten)	(None, 4608)	0
dense_64 (Dense)	(None, 256)	1179904
dropout_32 (Dropout)	(None, 256)	0
dense_65 (Dense)	(None, 1)	257

Total params: 1,273,409
Trainable params: 1,273,409
Non-trainable params: 0

FEATURE MAPS OF CNN



FEATURE MAPS OF CNN

- The feature map is the output of one filter applied to the previous layer.
- It incorporates all information in the first layer, but as it progresses further into the layers, it focuses mostly on feature combinations, becoming increasingly complex.
- It utilises more filters as it progresses through the neural network to collect as many combinations as feasible.
- The dense layer employs the sigmoid activation function, which is commonly employed in binary classification and has a value range of 0 to 1.
- If the output of this layer is less than 0.5, the patient is considered healthy; if it is larger than 0.5, the patient is considered depressed.

RESULTS

- After evaluation and passing the images through CNN model we got an accuracy of 87.76 percent.

- Train accuracy: 0.9456
- Test accuracy: 0.8776

CONCLUSION

- Advances in deep learning and machine learning technologies are allowing for the development of brainwave-based depression prediction systems.
- It has been shown, that imaging EEGs and using them as CNN model input is more successful than giving the model RAW EEGs directly.
- This study shows how to use a CNN and an EEG-based image asymmetry matrix to create a deep-asymmetry approach. The proposed approach and classification model were used to categorise depressed patients and healthy people.
- Because the entire process is carried out without manual interference, it is more efficient.

THANK YOU!!