Detection of Postpartum Depression using EEG and Deep Learning

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Introduction

During pregnancy, women undergo significant physical and physiological changes that can lead to stress and anxiety. Postpartum depression (PPD) affects up to 15% of new mothers worldwide and can have negative consequences for both mothers and infants. Unfortunately, up to 50% of PPD cases go undiagnosed. Early detection is crucial for prevention and intervention. Previous studies have relied on surveys and self-report ratings, but these methods are subjective and require focused attention. Researchers have explored various classifiers to assess mental stress levels. By using machine learning algorithms on Electronic Health Record (EHR) data, primary prevention techniques can predict PPD risk factors and identify women in need of early intervention. Neuroimaging techniques, including EEG, offer real-time measurement of cognitive abilities and have potential in evaluating mental stress. Thus, EEG-based methodologies have the potential to overcome limitations of previous approaches and improve accuracy in detecting PPD.

Proposed System

The objective of this work is to diagnose PPD patients in a clinical context. Hence, we propose the development of an effective system to classify depressed mothers suffering from PPD from the normal ones, by performing depression level quantification to determine whether the patient is healthy, or suffering from mild or severe depression. This is done in order to recommend appropriate levels of medical intervention. This reliable multi-class classification tool has the potential to be utilised for community purposes, enabling timely medical intervention and treatment.

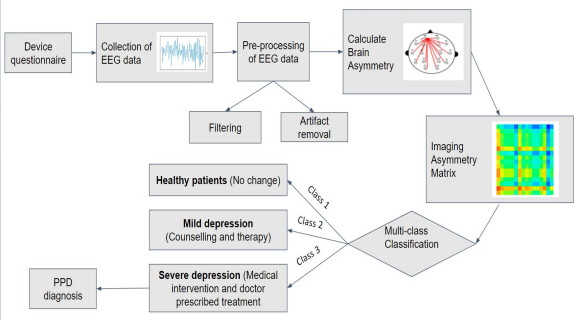

Fig 1. Proposed methodology for Postpartum depression (PPD) detection

Dataset Used

We constructed our own dataset by devising questionnaire based on the EPDS scale consisting of 10 questions of 3 points each to assess the subjects' levels of depression. Engaging a diverse group of participants, we collected their EEG signals while they answered the questionnaire using the ENOBIO-8 EEG acquisition system with electrodes placed in the pre-frontal cortex (considering Fp1, F3, F7, Fz, Fp2, F4 and F8 channels) while simultaneously being visualized using the NIC1 interface.

Subsequently, the EEG recordings were segregated by labelling them corresponding to the EPDS score range given as follows:

0-13 → healthy,14-19 → moderately depressed, 20-30 → severely depressed

Therefore, 14 healthy controls, 9 mildly depressed patients and 13 severely depressed patients formed part of our dataset.

Methodology

1) Data Preprocessing

The EEG recording files obtained were of .edf format. Hence, the MNE-Python package & sklearn were used here. The steps involved were as follows:

- Bandpass filtering (0.1-70Hz) = allows signals within a selected range of frequencies to be heard or decoded, while preventing signals at unwanted frequencies from getting through
- Notch filtering (50 Hz) = a type of band-stop filter, which is a filter that attenuates frequencies within a range while passing all other frequencies unaltered. This was to suppress power line noise.
- Min-Max Normalization = such that EEG data is normalized before use so each channel would have similar amplitude scaling.
- Independent Component Analysis (ICA) = used for removing EEG noise components arising from transient or large-amplitude artifacts such as eye blinking and muscle movement. Here, fastICA is performed.

2) Feature Extraction

The following protocol was established for feature extraction:

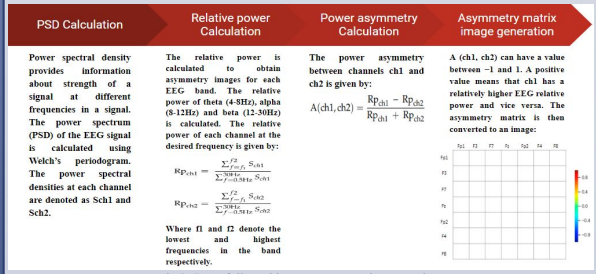

Fig 2. Steps followed in Feature extraction procedure

3) Multi-class classification

A CNN sequential model is built for multi-class classification of brain asymmetry images into 3 classes.

The final output from the dense layer gives the class corresponding to the image as either Class 1 (healthy), Class 2 (mildly depressed) or Class 3 (severely depressed).

Those classified into Class 3 are tagged as mothers suffering from PPD, which helps in its accurate diagnosis.

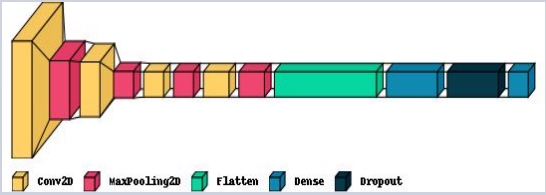

Fig 3. CNN model architecture

Results

The resulting asymmetry matrix images for the three classes were obtained as follows:

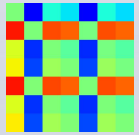

Fig 4.1 Class 1 (Healthy)

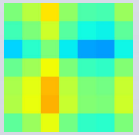

Fig 4.2 Class 2 (Mildly depressed)

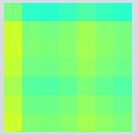

Fig 4.3 Class 3 (Severely depressed)

Figure 5.1 & 5.2 indicate how well the CNN model built fits the new data based on *theta wave* by observing the steady increase in validation accuracy and gradual decrease in validation loss over 100 epochs.

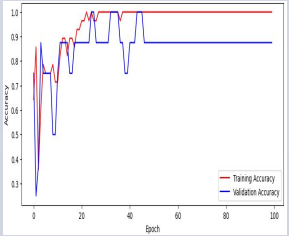

Fig 5.1 Training vs Validation accuracy

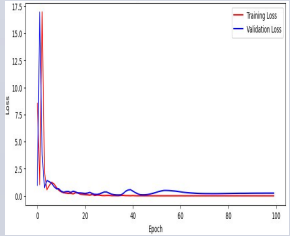

Fig 5.2 Training vs Validation loss

For performance comparison with our trained PPD model, pre-trained Keras models for image classification namely VGG16, VGG19 and Xception are used.

Our model shows comparative performance to other state-of-art multiclass image classification Keras models with superior speed per step. It can also be observed that Theta wave asymmetry shows better performance as compared to Beta wave asymmetry.

Table 1: Model performance comparison

Model	Test accuracy	Model	Test accuracy
VGG16	a) Theta = 0.875 b) Beta = 0.75	Xception	a) Theta = 0.75 b) Beta = 0.75
VGG19	a) Theta = 0.75 b) Beta = 0.75	Our PPD model	a) Theta = 0.875 b) Beta = 0.75

Conclusion

The current approaches for diagnosing PPD are labor-intensive and reliant on the doctor's experience. The patient's non-compliance due to fear of social stigma may lead to late or incorrect diagnosis. Our work suggests a multi-class image classification approach that combines a CNN with an EEG-based image asymmetry matrix. The PPD model thus built distinguishes between healthy mothers and those suffering from mild and severe depression with an accuracy of 0.875 using Θ wave asymmetry and 0.75 using β wave, showing comparative performance with other state-of-the-art pre-trained models. It can thereby diagnose for PPD in an objective & consistent manner. Medical practitioners can make use of such an automatic system as it has the potential to be used as an effective pre-screening tool for PPD detection.