EEG 우울증 분류를 위한 위상 잠금 값 기반 샴 네트워크

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Phase Locked Value-Based Siamese Network For EEG Depression Classification

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ABSTRACT

Mental health conditions such as Major Depressive Disorder (MDD) undoubtedly pose severe life-threatening effects if not properly diagnosed and treated promptly. In this paper, we aim to differentiate depressed patients from healthy controls by determining the level of co-functionality relationships between brain regions using the Multi-modal Open Dataset for Mental Disorder Analysis (MODMA) 128-channel resting-state Electroencephalography (EEG) data. By proposing a method that adopts the combination of Phase Locking Value (PLV) functional connectivity analysis with a Contrastive Siamese Network model, we extract PLV-based features and employ the proposed Contrastive Siamese Network to learn discriminative features from the PLV matrices. Our proposed approach achieved an accuracy of 0.88, surpassing prior research works on the same dataset. The results suggest that PLV can serve as a reliable biomarker for depression detection, effectively distinguishing between both classes and leading to robust classification outcomes.

1. Introduction

Major Depression Disorder (MDD) has proven to be one of the most pervasive mental health conditions, affecting millions of people worldwide. Usually characterized by persistent feelings of sadness, lack of interest, and behavioral impairments that can lead to a severe impact on an individual's quality of life [1]. Due to the subjectivity of self-reported symptoms from patients, the effective early diagnosis accuracy of this condition remains a challenge. As an effect, there is a growing interest in utilizing neuroimaging techniques, such as Electroencephalography (EEG), for the development of objective biomarkers for depression diagnosis.

EEG reliably captures the brain’s electrical activities through scalp electrodes thereby offering a non-evasive and cost-effective means of studying brain functions [2]. Functional connectivity analysis on the other hand has emerged as a valuable tool in the understanding of neural activity synchronization between different brain regions [3]. Alterations in these synchronizations between different brain regions and bands in depressed patients suggest that these brain network changes may serve as potential biomarkers.

Recently, due to the advancements in Machine Learning (ML), there has been a breakthrough in this research area opening up new avenues for analyzing complex neural data. Over the years, traditional classifiers such as k-nearest Neighbors (KNN) and Support Vector Machines (SVM) were extensively used for various mental health diagnoses with EEG data. However, Deep Learning (DL) architectures such as Convolutional Neural Networks (CNN), show superior learning discriminative features from high-dimensional data [4].

In this paper, we investigate the outcome of the combination of the Phase Locking Value (PLV) functional connectivity analysis method with a Contrastive Siamese Network model to determine the level of co-functionality between brain regions for the detection of depression using

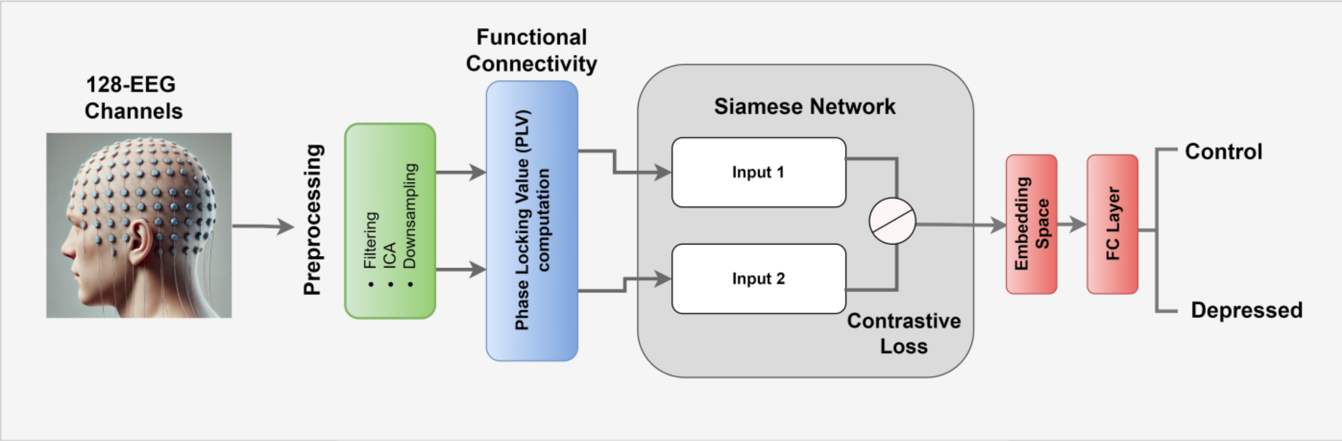

Figure 1. Proposed PLV+CSnet Model Architecture

resting-state EEG data.

Hypothetically, we believe that the functional connectivity differences between MDD patients and healthy controls, along with the powerful feature extraction capabilities of the Siamese network will lead to robust classification performances.

2. Dataset

The dataset used in this study is the Multi-modal Open Dataset for Mental Disorder Analysis (MODMA) 128-channel resting-state EEG dataset [5]. This dataset was collected from 24 individuals diagnosed with Major Depressive Disorder (MDD) and 29 healthy controls. Each participants were carefully screened based on the already-established Diagnostic and Statistical Manual of Mental Disorders (DMS).

All signals were recorded using the 128-channel HydroCel Geodesic Sensor Net to provide high-resolution coverage of the brain's electrical activity using the 10-5 electrode placement system during a resting-state EEG session to observe intrinsic brain activity and identify neural markers of depression.

2.1 Preprocessing

2.1.1 *Independent Component Analysis (ICA)*

A bandpass filter was applied to focus on relevant brain oscillatory rhythms while eliminating low-frequency drift and high-frequency noise. Next, we apply Independent Component Analysis (ICA) to detect and remove unwanted artifacts to maintain accurately represented neural activity.

Following this, we performed re-referencing while retaining 128 channels for analysis and finally performed epoch segmentation dividing the EEG data into shorter, artifact-free epochs focusing on stable brain states for Phase Locking Value (PLV) computation.

2.1.2 *Phase Locking Value (PLV)*

To measure the functional connectivity between brain regions we utilized PLV by quantifying phase synchronization between EEG channels. PLV quantifies the consistency of the phase difference between two signals over time, thereby serving as an effective measure of neural coherence and communication across brain regions. PLV is given by the formula below.

$$PLV_{ij}^{band} = \left| \frac{1}{T} \sum_{t=1}^{T} e^{i\left(\Delta\phi_{ij}^{band}(t)\right)} \right|$$

Where:

- PLV_{ij}^{band} represents the phase-locking value between electrodes i and j in a given frequency band.
- T is the number of time points in our analysis.
- $\Delta\phi_{ij}^{band}(t) = \phi_i^{band}(t) - \phi_j^{band}(t)$ represents the phase difference between the signals from channels i and j at the time point t in the specified frequency band.
- $\phi_i^{band}(t)$ and $\phi_j^{band}(t)$ are the instantaneous phases of the filtered EEG signals from electrodes i and j at time t, obtained via the Hilbert transform.
- Finally, the absolute $|\cdot|$ value ensures PVL remains a measure of phase consistency between 0 and 1 with 0 indicating no synchronization, and 1 indicating perfect synchronization (phase locking).

For both classes of control and patient groups, PLV was used on all pairs of the 128 electrode EEG channels thereby resulting in a 128x128 PLV matrix per subject across different frequency bands of neural oscillations (Delta, Theta, Alpha, Beta, and full band) to assess band-specific connectivity patterns related to depression.

It is worth noting that, for this study, our experiment was conducted only on the full frequency band for initial research analysis purposes.

3. Model Architecture

We propose a Contrastive Siamese Network model; PLV+CSnet to learn the feature representations from the preprocessed EEG signals (Figure 1).

Our Contrastive Siamese Network model is composed of two mirrored inputs made up of 2 convolutional layers of 3x3 kernel sizes followed by the ReLu activation function, and

MaxPooling layers respectively. These feature maps from the CNN layers are flattened and processed further through 2 fully connected layers.

Contrastive loss is applied at the end of both input paths of the Siamese network to train the model by adjusting the embeddings thereby ensuring that similar pairs are closer together. This minimizes the Euclidean distance between similar pairs and maximizes the distance between dissimilar pairs. Our contrastive loss function is computed as follows:

$$\boldsymbol{L = (1 - Y) \cdot \frac{1}{2} \cdot D^2 + Y \cdot \frac{1}{2} \cdot max(0, m - D)^2}$$

Where Y is a binary label indicating the similarity or dissimilarity between pairs, D is the Euclidean distance between embeddings of input pairs, and m is the separation margin of dissimilar pairs which ensures the distance between dissimilar pairs is at least m.

After training the Siamese network using contrastive loss, we obtain a learned embedding space that captures meaningful features that are then passed to the final fully connected layer with the SoftMax function to output class probabilities.

Our model takes a 128x128 PLV matrix as input and outputs the mental state of depression or control. Table 1 shows a detailed breakdown of the mirrored Siamese network section of our PLV+CSnet model architecture.

Table 1. Mirrored Layer-wise Breakdown of the Siamese Network layer of the PLV+CSnet

Input 1	**Input 2**
Input 128x128 PLV matrix	Input 128x128 PLV matrix
Conv2D 64 filters, 3x3 kernel	Conv2D 64 filters, 3x3 kernel
ReLu	ReLu
Conv2D 128 filters, 3x3 kernel	Conv2D 128 filters, 3x3 kernel
ReLu	ReLu
MaxPool2D 2x2 window	MaxPool2D 2x2 window
Flatten	Flatten
FC Layer 256 units	FC Layer 256 units
ReLu	ReLu
FC Layer 128 units	FC Layer 128 units

4. Result

Our proposed Contrastive Siamese network model trained on PLV features demonstrated reasonable performance in differentiating between Major Depressive Disorder (MDD) patients and Healthy Control (HC). To illustrate our model's performance, we performed a comparison analysis of our model accuracy results with prior studies on the MODMA dataset. Table 2 shows our comparison results with three other experiments where our model achieved a superior classification accuracy of 0.88.

Table 2. Model Performance Comparison

Research	**Method**	**Accuracy**
Ksibi et al. [6]	RF XGBoost	0.76 0.81
Shen et al. [7]	mKTAChSel + SVM	0.82
Sun et al. [8]	PLI+LR L&PLI+LR NL&PLI+LR ALL+LR	0.82 0.81 0.82 0.82
Our Model	PLV+CSnet	**0.88**

As shown in Figure 2a, our training and validation accuracy improved consistently as epochs progressed stabilizing as the model converged. While more erratic, our validation accuracy indicates an upward trend, establishing our model's ability to generalize across unseen data.

Figure 2a. Training/Validation accuracy

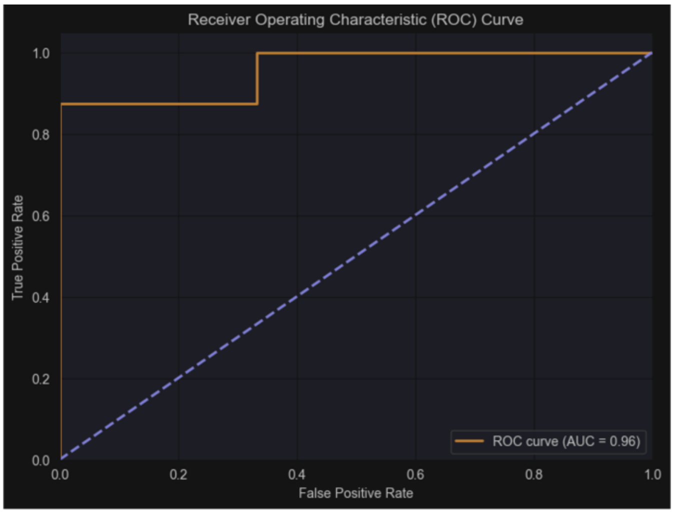

Figure 2b. Receiver Operator Characteristics (ROC) curve

Likewise, in Figure 2b, the Receiver Operator Characteristics (ROC) reveal an excellent classification capability. With an AUC of 1.0, our model illustrates a near-perfect model in terms of sensitivity and specificity when distinguishing between MDD patients and control subjects.

These results demonstrate our model's capability to effectively distinguish between cases of MDD and control subjects at various thresholds.

5. Conclusion

In this study, we investigate the use of Phase Locking Value (PLV) for functional connectivity analysis with a Contrastive Siamese Network for the detection of Major Depressive Disorder (MDD) using 128-channel EEG signal data.

Our findings validate our hypothesis that functional connectivity and our proposed Contrastive Siamese Network reveal significant differences between MDD patients and healthy controls, specifically aligning with existing research on depression-related brain connectivity changes over time leading to robust classification performance.

Our study further suggests the exploration of additional connectivity metrics and more analysis of other frequency bands to assess band-specific connectivity patterns as they relate to the functioning of depression with EEG signals.

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