EEG-BBNet: A Hybrid Framework for Brain Biometric Using Graph Connectivity

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Abstract—Most EEG-based biometrics rely on either convolutional neural networks (CNNs) or graph convolutional neural networks (GCNNs) for personal authentication, potentially overlooking the limitations of each approach. To address this, we propose EEG-BBNet, a hybrid network that combines CNNs and GCNNs. EEG-BBNet leverages CNN’s capability for automatic feature extraction and the GCNN’s ability to learn connectivity patterns between EEG electrodes through graph representation. We evaluate its performance against solely CNN-based and graph-based models across three brain–computer interface tasks, focusing on daily motor and sensory activities. The results show that while EEG-BBNet with Rho index functional connectivity metric outperforms graph-based models, it initially lags behind CNN-based models. However, with additional fine-tuning, EEG-BBNet surpasses CNN-based models, achieving a correct recognition rate of approximately 90%. This improvement enables EEG-BBNet to adapt its learning in new sessions and to acquire different domain knowledge across various BCI tasks (e.g., motor imagery to steady-state visually evoked potentials), demonstrating promise for practical authentication.

Index Terms—Sensor applications, brain biometrics, deep learning (DL), EEG, functional connectivity, graph convolutional neural network (GCNN).

I. INTRODUCTION

The need for biometric-based personal authentication using face, fingerprint, or voice has grown over decades to the point where it is embedded in practically every digital object we own [1]. However, these features remain vulnerable to spoofing attacks, such as faking fingerprints and bypassing face scans with photos [2]. Biometric data specific to individuals and not easily accessible, such as brain signals, then becomes a solution known as brain biometrics [3].

Traditionally, nondeep learning (DL) approaches for EEG brain biometrics relied on conventional machine learning methods, which often required handcrafted feature extraction. This approach demanded extensive domain knowledge and limited system flexibility [4]. In contrast, recent advancements in DL, particularly with convolutional neural networks (CNNs), have transformed the field by enabling the automatic learning of discriminative features directly from raw EEG data. However, CNNs fall short in capturing global functional relationships between EEG electrodes, an aspect critical for enhancing personal authentication, as highlighted by neuroscience research [5].

Graph convolutional neural networks (GCNNs) address this issue by modeling relationships between EEG electrodes and using hierarchical structures to extract graph domain features [6]. However, GCNNs have the limitation of losing valuable raw EEG data during graph construction. While the fusion of CNNs and GCNNs has shown promise in image-based EEG emotion recognition [7], it remains unclear how to combine the complementary aspects of EEG signals effectively. Moreover, this hybrid approach is underutilized in EEG-based biometrics for motor and sensory activities crucial for personal authentication, such as hand movement and gaze.

This gap has motivated us to propose an ongoing EEG biometric approach, EEG-BBNet, which represents EEG signals as dual features with both local and global functions through a combination of CNN and GCNN networks, aiming to leverage more comprehensive information from EEG data. EEG-BBNet is evaluated across three brain–computer interface (BCI) tasks: motor imagery (MI), event-related potential (ERP), and steady-state visually evoked potential (SSVEP), and is assessed for both classification performance and practicality, demonstrating its potential for reliable user authentication. We also publish the source codes of this work on GitHub. The repository will be publicly accessible after the paper’s acceptance.

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II. METHODS

A. Dataset and Preprocessing

We conduct our experiments using the OpenBMI EEG dataset [8] as our benchmark. In total, 54 healthy subjects participated in the experiment, performing three EEG BCI tasks: MI, ERP, and SSVEP. The EEG was acquired using the BrainAmp EEG amplifier with 64 electrodes at a 1 kHz sampling rate. Each subject performed each task twice on two days (sessions I and II).

Our analysis utilizes only the data from the offline phase of the dataset. The EEG signals are bandpass filtered between 3 and 40 Hz using a 5th order Butterworth filter and then downsampling to 250 Hz. All trials of MI and SSVEP tasks have the same length of 4 s. Hence, the number of time samples ($T$) per trial is $T = 1000$. The ERP task is 0.8 s long; therefore, $T = 200$.

B. EEG-Graph Representation

An undirected weighted graph is represented by $G = (V, E)$ where $V$ indicates a set of nodes and $E$ represents a set of edges or relationships between the nodes in $V$. The edges $E$ in the graph $G$ can be represented by the weighted adjacency matrix $A \in \mathbb{R}^{N \times N}$ where $N$ denotes the number of nodes in $G$. An element of $A$ at the $(k, l)$ location reflects the relationship between node $k$ and node $l$.

The nodes in $V$ represent the scalp electrodes for EEG-Graph representation, so $N = 62$ in our study. Each node contains the features extracted from the raw EEG data recorded by that electrode. The weight of each edge in $E$ reflects pairwise connectivity between data from two electrodes.

EEG-graph representation analysis [9] employs various connectivity measures to examine relationships between signals from multiple perspectives, including linear correlation in the temporal domain and phase synchronization. In this letter, we explore these metrics for comparison. Specifically, Pearson’s correlation coefficient is used for temporal correlation, while phase synchronization is assessed using three measures: phase locking value, phase-lag index (PLI), and the RHO index. Each metric is described below.

1) Pearson’s Correlation Coefficient (COR): Let $x_k(t)$ and $x_l(t)$, $t = 1, \ldots, T$ represent the $T \times 1$ time series of EEG signals from electrodes $k$ and $l$, respectively. The Pearson’s correlation coefficient $r \in [-1, 1]$ is given by

$$r(k, l) = \frac{1}{\sqrt{\sum_{t=1}^{T}(x_k(t) - \bar{x}_k)^2} \sqrt{\sum_{t=1}^{T}(x_l(t) - \bar{x}_l)^2}} \sum_{t=1}^{T}(x_k(t) - \bar{x}_k)(x_l(t) - \bar{x}_l)$$

where $\bar{x} = \frac{1}{T} \sum_{t=1}^{T} x(t)$ is the time-average of $x(t)$.

Since EEG signals are rhythmic oscillations, we can extract more information from phase synchronization. The phase synchronization $\Delta \phi(k, l)$ is defined as the relative phase between the two signals $x_k(t)$ and $x_l(t)$, and is given by

$$\Delta \phi(k, l) = |\phi_k(t) - \phi_l(t)| \mod 2\pi.$$

The phase $\phi_k(t)$ is obtained by performing a Hilbert transform on $x(t)$. In this work, we extract three commonly used measures from phase synchronization [9].

2) Phase-Locked Value (PLV): The PLV estimates how the relative phase is distributed over the unit. It is expressed as

$$\text{PLV}(k, l) = \left| e^{i\sum_{t=1}^{T}\Delta \phi_k(t)} \right| = \left| \frac{1}{T} \sum_{t=1}^{T} e^{i\Delta \phi_k(t)} \right|.$$

3) Phase-Lag Index (PLI): This measure determines the time-lagged interdependence of two signals based on their relative. It also represents the relative phase distribution. Define sign as the signum function, the PLI is computed from

$$\text{PLI}(k, l) = \left| \frac{1}{T} \sum_{t=1}^{T} \text{sign}(\Delta \phi_{k,l}(t)) \right|.$$

4) Rho Index (RHO): This index is based on Shannon entropy [10]. It quantifies the cyclic relative phase distribution deviation from the uniform distribution. The discrete version is defined as

$$\text{RHO}(k, l) = 1 - \frac{S}{S_{\text{max}}}$$

where $S_{\text{max}} = \ln T$ is the maximal entropy of the uniform distribution quantized into $T$ bins and $S$ is the entropy of relative phase.

C. Graph Convolution Neural Networks

Graph convolution neural network is commonly used due to its capabilities in learning through connections between nodes in a graph [11]. It trains the network using graphs as input. The convolution operation of GCNN produces a normalized sum of features from neighboring nodes. For a graph $G$ consisting of $N$ nodes with $F$ features per node, its propagation layer is defined as

$$H_n+1 = \sigma(\hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}}H_nW_n)$$

where $\hat{A} = A + I_N$, $A$ is the adjacency matrix, and $I_N$ is the $N \times N$ identity matrix. $H_0$ is an input matrix of layer $n$, and $H_0$ is the initial input. $W_n$ is the trainable network parameters of layer $n$. $\hat{D}$ is a diagonal degree matrix of nodes used to normalize $\hat{A}$, $\sigma$ is the nonlinear activation function.

D. EEG-BBNet Implementation

The structure of EEG-BBNet is illustrated in Fig. 1. In the beginning, the preprocessed EEG signals are fed into two workflows. The first workflow employs depthwise separable convolutions (DepthwiseConv2D), which apply a distinct filter to each input channel and are frequently paired with pointwise convolutions to combine outputs from various channels. We have chosen to implement DepthwiseConv2D layers in EEG-BBNet to ensure that each EEG channel’s unique characteristics are independently processed and represented. This method extracts $F$ features from each electrode, reducing computational load and parameters, thus enabling faster training [12]. Each layer in this workflow applies a distinct 64-sized kernel filter to each input channel independently. This layer performs a separate convolution for each input channel. These channel-specific features are precious for constructing a graph, where each feature vector is derived from an individual EEG channel. This approach is crucial since the graph convolutional network model (GCN) component requires data that representatively captures the information from each N channel. The EEG signals are fed into two DepthwiseConv2D layers with batch normalization and max pooling layers with a size of 32. Moreover, to combat overfitting, a dropout rate of 0.2 is implemented after each pooling operation.

The second workflow involves the construction of a graph. Concurrently, the EEG signals compute one of the connectivity measures described in Section II-E and construct the $N \times N$ weighted adjacency matrix $A$. The CNN feature matrix and the adjacency matrix are combined to produce the final graph. In the second stage of EEG-BBNet, the graph from the first component acts as the initial input for graph convolution (GC), i.e., $H_0$ in (6). It contains two graph.
convolution (GConv) layers, the output of which continues into the last segment of EEG-BBNet, including the fully connected layers for personal authentication. We use the rectified linear unit as the activation function $\sigma(\cdot)$ for every layer except the last one, which uses Softmax to identify the owner of the EEG signals. The network is optimized using Adam optimizer with a learning rate of 0.001 and a cross-entropy loss function.

We used five-fold cross-validation in all experiments with the 70:10:20 ratio for training, validation, and testing sets. We compute the correct recognition rate (CRR) and report its mean and standard deviation.

### E. Baseline Approaches

1) **Solely CNN-Based Models:** We chose two solely CNN-based approaches for evaluation. The first approach utilizes a CNN, where EEG signals are processed through a stack of 2D CNN layers for feature extraction, each employing $3 \times 3$ kernels. This architecture includes layers with 512, 256, 128, 64, and 32 filter counts, with batch normalization applied at each layer. The workflow concludes with fully connected layers and a softmax function for pattern authentication.

The second approach combines CNN with long short-term memory (CNN+LSTM) models, building on the LSTM’s proven effectiveness in temporal feature extraction as demonstrated in previous work [13]. This model starts with three layers of 2D CNN applied to the mesh structure. Each sliding window, treated individually with shared parameters, uses a time-distributed 2D-CNN layer. Next, a time-distributed, fully connected layer performs subsampling and feature transformation. Importantly, the LSTM layers capture the temporal dynamics across these sliding windows, and rather than predicting a sequence, the model concludes with a fully connected layer and a softmax function tailored for the final identification task.

2) **Solely Graph-Based Model:** This approach as demonstrated at previous work [14]. This method employs a graph representation that transforms EEG signals from electrodes into a functional connectivity graph (e.g., PLV and COR). The resulting graph is then processed by a GCNN-based classification component to learn distinctive patterns within the EEG graphs for EEG-based person identification.

### III. RESULTS

To determine if EEG-BBNet outperforms models trained solely on CNN or GCNN-based approaches, we compared them against these baseline models. The evaluation was divided into three experiments: Experiment I focused on classifying data from specific tasks. In contrast, Experiments II and III demonstrated the practicality of EEG-BBNet by training and testing it across different sessions and tasks, respectively.

#### Experiment I: Specific tasks classification

As Table 1 shows, EEG-BBNet underperformed compared to the solely CNN-based models for MI and SSVEP tasks but outperformed the GCN models across all tasks with different connectivity metrics. This suggests that while combining CNN and GCN can improve performance, it is still less effective than using CNN alone for specific tasks. However, we cannot conclude that EEG-BBNet is inferior based on these results alone. EEG-BBNet needs more practical assessment. Therefore, we conducted cross-session and cross-task tests to evaluate the robustness and flexibility of EEG-BBNet in the following experiment.

#### Experiment II: Cross-sessions classification

To demonstrate the robustness of the model across sessions, in this experiment, we trained the model using data from session I and tested it on data from session II.

We initially obtained the best CRRs from EEG-BBNet[RHO], but they were only about 18%–30% for ERP, MI, and SSVEP tasks. These low CRRs were expected since data from different sessions can be quite divergent. To improve these rates, we fine-tuned the model by methodically adding 5% increments of session II data, which was previously segmented into 20 equal parts after separating the validation and test sets.

Fig. 2 shows the CRRs of EEG-BBNet[RHO], EEG-BBNet[COR], CNN, CNN+LSTM, and GCN[PLV], which is the best GCN connectivity in this experiment. EEG-BBNet[COR], CNN+LSTM, and especially EEG-BBNet[RHO] are comparable when fine-tuning data exceeds 35% in all tasks. Interestingly, GCN[PLV] benefits significantly less from this than the others.

The results suggest that the EEG-BBNet[RHO] demonstrates effective adaptation to new sessions with additional fine-tuning data, highlighting its robustness.

#### Experiment III: Cross-tasks classification

To assess the model’s flexibility across entirely different domains, we trained it on MI data and evaluated it on SSVEP data and vice versa.
The same network architecture was used because MI and SSVEP data have identical dimensions.

Fig. 3(a) shows that EEG-BBNet[RHO], EEG-BBNet[COR], and CNN are comparable after 10% fine-tuning when these models were trained with SSVEP data and tested on MI data. Conversely, Fig. 3(b) shows that when trained with MI data and tested on SSVEP data, EEG-BBNet[COR] and EEG-BBNet[RHO] perform slightly lower than the solely CNN-based models within the same fine-tuning range. However, the differences in their performances were insignificant. These results suggest EEG-BBNet is quite flexible.

IV. DISCUSSION

This work proposes EEG-BBNet, which combines the benefits of CNN and GCNN. It consistently outperforms models trained solely on GCN and shows strong adaptability to new sessions when provided with additional fine-tuning data. These results underscore their robustness and flexibility compared to other baselines, with EEG-BBNet [RHO] proving the most effective, with its effectiveness likely due to its ability to extract phase information from the oscillatory behavior of EEG signals, rather than capturing electrode correlations as done by COR.

EEG-BBNet excels in personal identification but faces challenges. To improve, we propose the following future directions and solutions. First, it struggles with cross-task classification due to domain shifts between MI and SSVEP data. Feature extraction from pretrained models can help address this [15]. Second, EEG-BBNet does not generalize well across sessions when without fine-tuning. Using a signal decomposition method [16] could help the model learn underlying patterns. Third, EEG-BBNet relies on multichannel data, which is incompatible with wearable sensors. Future research should explore using exponential variation in the depth multiplier along with kernel size [17] to handle fewer EEG channels. Lastly, the small sample size limits the model’s generalization. Increasing the number of participants could enhance performance [18].

V. CONCLUSION

We introduced EEG-BBNet, which combines CNN and GCNN for enhanced EEG-based BCI data analysis. While it outperformed GCNNs across all tasks, it performed worse than CNN models on some tasks. With fine-tuning, EEG-BBNet surpassed CNN models and adapted better to different sessions and tasks (e.g., SSVEP to MI). However, transferring features across certain BCI datasets remains a challenge that requires further improvement.

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