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EEG-based image classification using an efficient geometric deep network based on functional connectivity

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ABSTRACT

To ensure that the FC-GDN is properly calibrated for the EEG-ImageNet dataset, we subject it to extensive training and gather all of the relevant weights for its parameters. Making use of the FC-GDN pseudo-code. The dataset is split into a "train" and "test" section in Kfold cross-validation. Ten-fold recommends using ten folds, with one fold being selected as the test split at each iteration. This divides the dataset into 90% training data and 10% test data. In order to train all 10 folds without overfitting, it is necessary to apply this procedure repeatedly throughout the whole dataset. Each training fold is arrived at after several iterations. After training all ten folds, results are analyzed. For each iteration, the FC-GDN weights are optimized by the SGD and ADAM optimizers. The ideal network design parameters are based on the convergence of the trains and the precision of the tests. This study offers a novel geometric deep learning-based network architecture for classifying visual stimulation categories using electroencephalogram (EEG) data from human participants while they watched various sorts of images. The primary goals of this study are to (1) eliminate feature extraction from GDL-based approaches and (2) extract brain states via functional connectivity. Tests with the EEG-ImageNet database validate the suggested method's efficacy. FC-GDN is more efficient than other cutting-edge approaches for boosting classification accuracy, requiring fewer iterations. In computational neuroscience, neural decoding addresses the problem of mind-reading. Because of its simplicity of use and temporal precision, Electroencephalographys (EEG) are commonly employed to monitor brain activity. Deep neural networks provide a variety of ways to detecting brain activity. Using a Function Connectivity (FC) - Geometric Deep Network (GDN) and EEG channel functional connectivity, this work directly recovers hidden states from high-resolution temporal data. The time samples taken from each channel are utilized to represent graph signals on a topological connection network based on EEG channel functional connectivity. A novel graph neural network architecture evaluates users' visual perception state utilizing extracted EEG patterns associated to various picture categories using graphically rendered EEG recordings as training data. The efficient graph representation of EEG signals serves as the foundation for this design. Proposal for an FC-GDN EEG-ImageNet test. Each category has a maximum of 50 samples. Nine separate EEG recorders were used to obtain these images. The FC-GDN approach yields 99.4% accuracy, which is 0.1% higher than the most sophisticated method presently available

Keywords: EEG, Visual Stimulus Decoding, Functional Connectivity, Deep Learning, Neural Network

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1. Introduction

Large clusters of neurons may now be recorded [1]. Researchers created noninvasive brain activity measurements. Research uses electroencephalograms (EEGs) because of their inexpensive cost and great temporal precision. Brain stimulation and impact change fast. Neuroscience research like BCI deciphers EEGs depending on inputs. Since vision is a fundamental part of human experience, many neurocognitive research have examined the relationship between visual perception and brain activity. Visual stimuli cause different brain activity patterns [2][3][4]. Visual stimuli may be decoded to study human visual information processing [5]. Visual-brain decoding has two difficulties. Brain activity classification and stimulation are the first two steps. First, steady-state visual evoked potentials (SSVEPs) research, such as the BCI spelling system [6] has examined visual information processing by altering stimulus frequency. Results Another EEG study utilizing frequency-related visual stimulation found crowded objects [7]. EEG-based deep neural networks classified pictures [8]. These studies examined normal vision-related brain activity rather than visual input frequency. fMRI data can recreate pictures [9]. In 2018, [10] measured visual saliency using video stimulus EEG data. Dan Nemrodov and Adrian Nestor recreated facial emotions using EEG signals from face photo stimuli [11], followed by multimodal representation saliency detection [12] and Nicolae Cudlenco's [13]. EEG recordings of natural stimulations improve brain system comprehension. This research utilizes EEG-ImageNet [8]. For classification, BCI EEG classification algorithms have been studied. Deep learning, which combines feature extraction and classification, has garnered interest in recent years [14][15]. Deep machine learning is used by BCI in order to classify SCP, SSVEP, emotion detection, MVEP, sleep/weariness databases, epileptic EEG, and motor imagery are some of the techniques used. [16-22]. Graph-based categorization methods assessed EEG datasets. Geometric deep learning educated several graph neural network topologies. Geometric deep learning examines deep learning applications. [22]. M. Gori et al. created a graph neural network (GNN) to analyze graph data in 2005 [23]. In 2009, Scarselli et al. developed a technique for transforming graphs to Euclidean spaces and presented supervised learning for predicting graph neural network model parameters [24]. 2013 Bruna et al. suggested graph-based spectral convolutional neural networks [25]. Two years later, Bruna and Hennaf's graph estimation method created a new spectral network [26]. M. Defferrard et al. built ChebNet in 2016, whereas Kipf and Welling offered a smaller GCN [27][28]. Most geometric deep learning research graphs include EEG signal features. These studies used four course sets. [29] EEG-based emotion identification was assessed using DE, PSD, DASM, RASM, and DCAU characteristics. [29] classified emotions as pleasant, negative, or neutral. [30] suggested EEG electrode frequency-domain GNN and EEG-based video recognition. LSTM and GNN classified four motor imagery kinds [31]. Geometric deep learning techniques increase EEG-based item categorization, but they disregard dynamic information across linked EEG channels based on brain functional connectivity. They extract time-frequency information in two steps, which increases computing cost. An efficient EEG graph representation may solve the issues mentioned. EEG categorization might employ recordings and a deep network. Functional channel connections let this EEG data graph model classify EEG records. The proposed network architecture substitutes feature extraction with a geometric network that unifies feature extraction and classification, reducing computational complexity and improving classification accuracy with quicker convergence in fewer training cycles. This follows. Section 2 discusses graph convolution math. Section 3 discusses EEG-based image recognition and classification. Section 4 presents EEG-ImageNet, experimental results, and a comparison to current approaches. Fifth segment concludes.

1.1. Geometric deep network based on function-connectivity

The FC-GDN automatically identifies visual stimuli. Figure 1 shows a framework. First, the human subject is stimulated visually depending on the picture appearance time and image interval. Second, EEG data isolates Beta and Gamma frequency ranges associated with cerebral function. EEG channel functional connectivity is sparsely assessed using the spatiotemporal graph model. Network embedding vertices are assumed in EEG channel time samples. A functional adjacency matrix is the EEG channel connectivity matrix. Thresholds have a weak resemblance to the graph's adjacency matrix. The graph is sent to the FC-GDN. Graph convolution layers impose the preceding stage's graph to extract feature vectors in feature encoding. Feature vectors from a dropout and fully connected layer are used by log-soft-max classifiers. Labels are determined by the final categorization results.

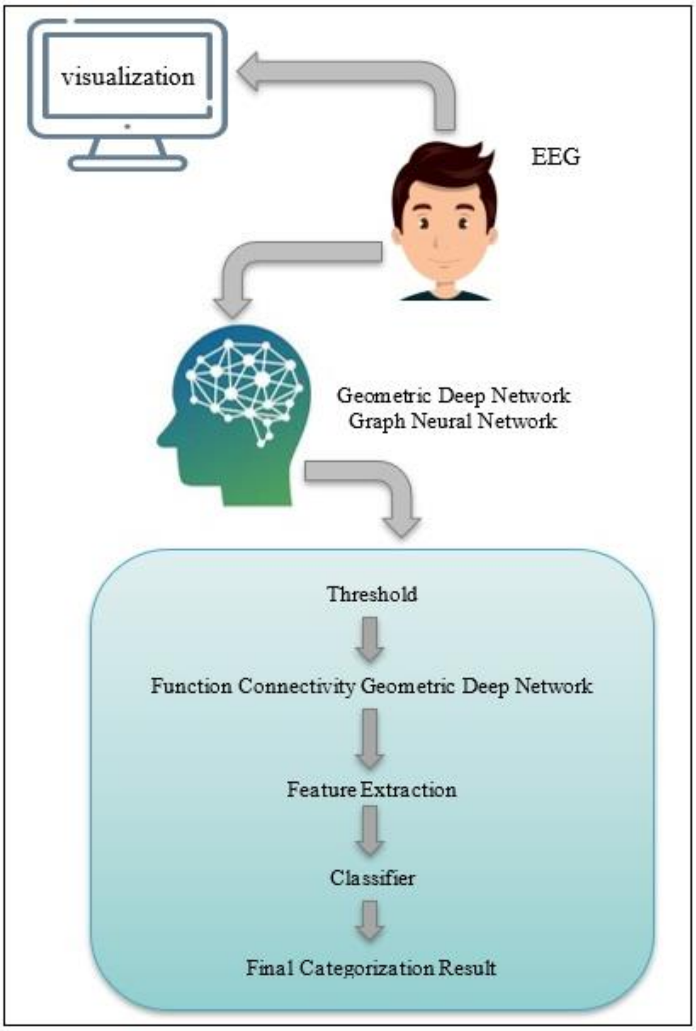

Figure 1. FC-GDN schematics

GDNs in the FC layer extract input category discrimination. Dynamic information must be provided via EEG channels coupled with graph convolutional layers. The initial step in every graph convolutional layer is to approximate the input graph convolution utilizing the graph Laplacian' polynomial expansion. Each layer's activation function, the rectified linear unit (ReLU), zeroes negative outputs. A batch normalizing filter applies each layer's output to the next. Normalization in batches expedites network training. Batch normalization outputs to graph convolutional layer, dropout layers prevent overfitting. After flattening the dropout layer output, dense fully connected layers get the feature vector. Finally, log soft max classifies output from entirely linked layers. Section 4.1 defines these characteristics based on the frequency and duration of EEG-sample ImageNet recordings. Because EEG signals comprise 166 channels, the FC-feature GDN encoding network in Fig. 1 includes 166 nodes. Since this dataset comprises 560 EEG channels, each network node processes 560 samples. The graph convolutional layer's input dimension is 560, regardless of network nodes. The first graph convolution layer has 560 vertex samples and 166 node samples. The second level constructs a network with 166 nodes and 220 samples for each vertex, while the construct networks with 160 and 50 samples for each node, respectively. The output of the feature encoding is transmitted to a layer that acts as a dropout then, 50 samples are used to flatten the 166-node network. Vectorization that contains 6400 different things. Due to the fact that the flattened vector passes through more than one layer, that is completely linked in order to fit the 60 Classifying EEG-ImageNet. The dense layer's input and output are 8400 and 60, respectively. The parameters for the FC-GDN layer weight tensor. The sequence in which the Chebyshev polynomial expansion is conducted on each layer determines the parameters of the graph's convolutional layers. FC-GDN parameter weights match EEG-ImageNet after training. FC-GDN code. validation divides train and test datasets. 25-fold divides dataset into 75% training set and 25% test set by choosing one fold per iteration as test split. This approach trains all 25 folds without overfitting. Much iteration converges on each training fold. Training all 25 folds evaluates performance. Train convergence and test accuracy are ideal network design criteria. Table 1 shows this.

Table 1. Overall accuracy result for various networks

Visual Category	FC-GDN($F1$ = 1, $F2 = 1$,	FC-GDN($F1$ $= 2, F2 = 2$,	BiLSTMs	LSTMs	SNN
’One’	100%	98%	95%	95.7%	92%
’two’	100%	99.7%	100%	98%	88.7%
’Three’	93.3%	82.3%	90.7%	94.7%	88.3%
’Four’	100%	99.3%	98.3%	93.8%	85.3%
’Five’	93.3%	90.7%	95.3%	90.3%	87%
’Six’,	100%	99.3%	97%	86.3%	86.3%
’Seven’	100%	98.7%	99%	87.7%	83%
’Eight’	100%	99.7%	98.7%	89.7%	87.3%
’Nine’	100%	96.3%	92.3%	89.3%	87%
’Ten’	93.3%	83.3%	85.7%	94.3%	83.3%
’Eleven’	100%	100%	99%	99%	91.7%
’Twelve’	100%	99.7%	96.3%	97.7%	86.3%
’ Thirteen’	93.3%	83.3%	100%	100%	98.7%
’ Fourteen’	100%	100%	93%	93.7%	89%
’Fifteen’	100%	98%	96.7%	85%	89.3%
’Sixteen’	100%	99.3%	99.7%	91%	92.7%
’Seventeen’	100%	99.7%	99%	87%	95%
’Eighteen’	100%	99.3%	99%	87.3%	91.7%
’Nineteen’	100%	99.3%	98.6%	93.2%	91.8%
’Twenty’	100%	100%	100%	84.7%	89%
’Twenty one’	100%	98.7%	99.7%	82.7%	84.7%
’Twenty two’	100%	98.3%	96%	86.3%	90.7%
’Twenty three’	100%	99.7%	96.3%	87.7%	88%
’Twenty four’	100%	98%	99%	88.7%	83%
’Twenty five’	100%	99%	99.7%	94.3%	85%
’Twenty six’	100%	100%	99.7%	89.8%	75%
’Twenty seven’	100%	100%	99.3%	85.3%	88.1%
’Twenty eight’	100%	99.3%	97%	88%	83%
’Twenty nine’	100%	95%	95.7%	87.7%	90.7%
’Thirty’	100%	97.3%	91.7%	82%	79.7%
’Thirty one’	100%	98.7%	100%	96%	83%
’Thirty two’	99.7%	100%	97.3%	87.3%	86.3%
’Thirty three’	100%	99.3%	98.3%	83.7%	85.7%
’Thirty four’	100%	98.9%	98.2%	88.4%	94.3%
’Thirty five’	100%	98.7%	96.7%	84%	79.3%
’Thirty six’	100%	100%	100%	95.7%	92.3%
’Thirty seven’	100%	100%	100%	88.3%	95.7%
’Thirty eight’	100%	98%	99.3%	85.3%	71.7%
’Thirty nine’	100%	100%	99.7%	85%	83.7%
’Forty’	100%	99.7%	99.7%	95.7%	92.3%
'Forty one'	100%	99.3%	81.9%	89.1%	80.1%
'Forty two'	99.8%	99.9%	93.5%	87.7%	88.4%
'Forty three'	100%	96.8%	90%	92.3%	90.1%
'Forty four'	100%	99%	88.1%	95.2%	89.1%
'Forty five'	100%	93.4%	89.9%	88.7%	87.6%
'Forty six'	100%	98%	95.6%	85.7%	83.4%
'Forty seven'	100%	96.3%	98.3%	90.3%	88.1%
'Forty Eight'	100%	92%	87.9%	87.2%	96.4%
'Forty nine'	100%	98.9%	88.7%	89.7%	80.8%
Fifty	100%	99%	90.8%	81.3%	88.9%
Overall Accuracy	99.4%	98%	91.33%	89.08%	84%

2. Methods

Many experiments will use perceive lab's EEG-ImageNet database [8][12]. After discussing database configurations, we discuss FC-outcome GDNs.

2.1. Database settings

Here's EEG-ImageNet. The actiCAP 128Ch collected EEG-ImageNet [32]. Depicts conventional helmet EEG installation. Table 2 provides color-ordered electrodes. EEG-ImageNet has six visual-stimulated human EEG signals. EEG signals were captured from 50 ImageNet pictures per category.In [8], Each photo was flashed on the computer screen for 700 milliseconds at 3kHz to record data.

2.2. Simulation results and discussion

The FC-GDN should be simulated. The EEG-ImageNet database from Section 4.1 is loaded on a desktop computer that has a Core i5 processor running at 4 GHz, 32 GB of RAM, and an NVIDIA GTX 1070 graphics processing unit (GPU). We average all EEG channel time-domain data to derive the topological map for each visual stimulus category. Electrode activation reveals mental activity during picture processing. EEG waves let individuals see their environment. The GDN matrix assesses EEG channel functional connectivity. We empirically balance sparsity/computational complexity with classification accuracy. channel sparsification. The graph's threshold was 0.5. To categorize the performance of the FC-Chebyshev GDN's polynomial expansion, a graph convolutional function based on Welling's [28] GCN with the same architecture is employed. Figure 2, 3 shows a side-by-side comparison of the FC-GDN and GCN with comparable dimensions. According to the results of our research example, FC-GDN converges faster than GCN and improved precision for training and testing phases.

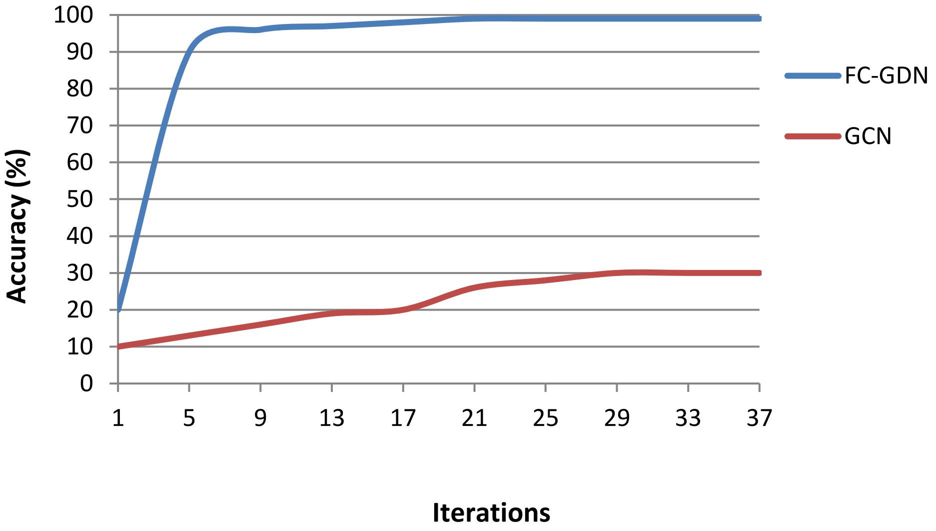

Figure 2. FC-GDN/GCN classification accuracy.

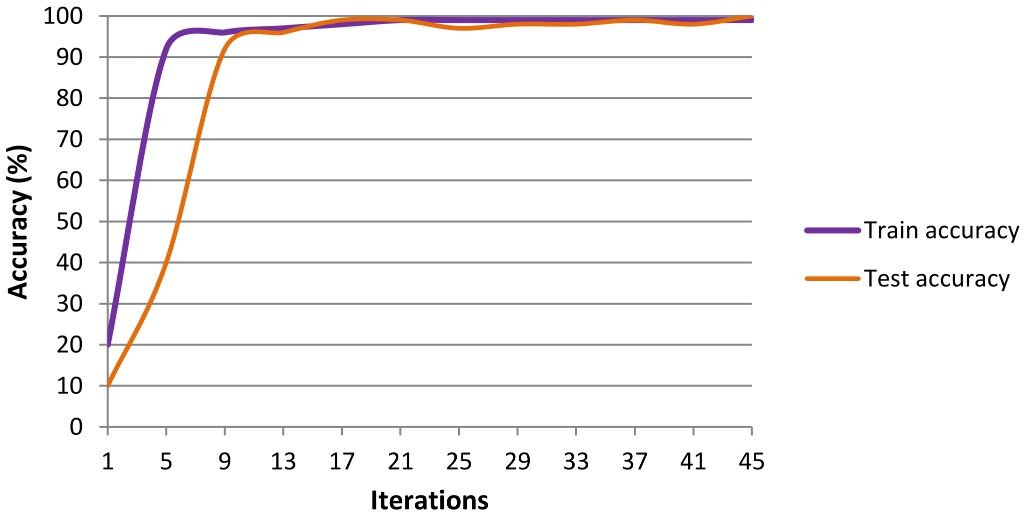

Figure 3. Accuracy for training and test phases

3. Result and discussion

Each training and testing iteration results in a smaller loss of cross-entropy, and by the tenth round, the two sets of results have converged. The FC-GDN achieves 99.4% accuracy after 12 iterations when classifying 50 distinct classes. The accuracy only marginally improves after 50 sessions. The confusion matrix helps the FC's performance. GDN's Network performance on test splits is reflected in the confusion matrix for multi-class classification. The proposed method's confusion matrix demonstrates the FC-high GDN's performance.

4. Conclusion

The loss of cross-entropy reduces with each iteration during training and testing and converges around the tenth iteration in both cases. After 12 iterations, the FC-GDN is able to classify a total of 50 categories with an accuracy of 99%. Even after 50 repetitions, there is still a tiny improvement in accuracy. This research introduces a novel geometric deep learning-based network architecture for classifying visual stimulation kinds using EEG data from human volunteers seeing photographs from each group. The major challenges addressed in this study are GDL-based feature extraction and functional connectivity brain state extraction. The strategy has been validated using EEG-ImageNet experiments. FC-GDN performs better with fewer iterations.

Conflict of interest

The authors declare that they have no conflict of interest, and all of the authors agree to publish this paper under academic ethics.

Author contributions

All the authors contributed equally to the manuscript.

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