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Dynamic Functional Connectivity Patterns in Resting-State EEG for Classifying Learning Strategies

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ABSTRACT
Dynamic functional connectivity (dFC) captures temporal variations in brain network interactions, offering deeper insights into cognitive processes compared to static connectivity measures. This study proposes a novel framework for classifying different learning strategies—control, active, and passive—using resting-state electroencephalography (EEG). Resting-state EEG data from twenty-one participants were preprocessed and analyzed using the Phase Lag Index (PLI) to compute functional connectivity across 18 EEG channels. Dynamic connectivity matrices were generated using sliding-window correlations, and their upper-triangular elements were vectorized to obtain subject-specific dFC features. Euclidean distance and multidimensional scaling (MDS) were applied for dimensionality reduction before classification. Statistical analyses, including paired and Welch's t-tests with Bonferroni correction, revealed significant within- and between-group differences ($p < 10^{-8}$). Machine learning models—K-Nearest Neighbors (KNN) and Random Forest (RF)—achieved classification accuracies exceeding 80% and 70%, respectively, in distinguishing both within- and between-group patterns. These findings demonstrate that dFC features from resting-state EEG can effectively differentiate learning strategies, reflecting distinct neural reorganization patterns associated with cognitive engagement. The proposed framework provides a foundation for exploring EEG-based biomarkers of cognitive processes and potential applications in educational neuroscience and clinical diagnostics.

General Terms
EEG, Machine Learning, Functional Connectivity

Keywords
EEG, dynamic functional connectivity, resting state, study methods, multidimensional scaling

1. INTRODUCTION
Functional connectivity (FC) is measured from resting-state fMRI data by correlating time series across brain regions over the whole scan, assuming stable connectivity throughout [1]. Functional connectivity indicates changes in the strength of connections between brain regions and networks, as observed in resting-state fMRI with increasing task demands [2]. This phenomenon is referred to as dynamic functional connectivity (dFC). Another research group has shown that the dynamic functional connectivity of the whole brain differs between rest and task data [3]. Many studies have developed methods to analyze dynamic functional connectivity in raw fMRI data using sliding-window correlations, both at the whole-brain level and in specific regions of interest [4, 5].

Previous studies using fMRI data have shifted toward examining resting-state networks through electroencephalography (EEG) signals. The researchers hypothesized a strong connection between resting-state network variability and working memory (WM) performance based on EEG data [6]. The study revealed that optimal working memory in individuals is shaped by the dynamic reorganization of functional brain modules, driven by temporal changes within resting-state networks. Another study shows that EEG can be used to measure resting-state and steady-state activity during a visuospatial working memory task before and after training [7]. EEG functional connectivity is useful in mental health research; one study found that Major Depressive Disorder patients with low baseline theta connectivity experienced greater improvement after four weeks of repetitive transcranial magnetic stimulation (rTMS) [8]. In a separate mental health study, the researchers identified EEG dynamic patterns within the spatiotemporal feature space that are unique to nonpsychotic major depression (NPMD), psychotic major depression (PMD), and schizophrenia (SCZ) [9]. Another research group demonstrated that EEG-based dFC can assess brain function at both population and individual levels, as its profile predicts gender and displays shared characteristics across individuals and hemispheres [10]. The research group found that EEG connectivity patterns in the beta band more clearly distinguish emotion groups than other bands, and these patterns change over time and relate to self-assessed emotional dimensions like arousal and dominance [11].

Accordingly, this research presents a novel framework for classifying different study approaches using resting-state dFC EEG data. The dFC features are extracted from control, active, and passive learning groups, and then applied to machine learning to classify both within and between groups. The detailed calculation of the dFC feature is in the methodology section, and we used the K-Nearest Neighbors (KNN) and random forests (RF) as machine learning frameworks for classification: binary (two groups) and multi (three groups).

2. DATA DESCRIPTION

A publicly available resting-state EEG dataset from openNeuro is used in this research [12]. This dataset contains EEG recordings that examine neural correlations of learning in educational settings. The dataset included 21 undergraduate students with typical neurodevelopment (mean age: 23.10 years, SD: 3.92) and was collected at the Federal University of Paraíba (UFPB), Brazil. Participants were randomly assigned to one of three different experimental groups. In the active learning group, participants completed a review session on the NeuroShow platform, which involved 10 retrieval-practice questions with immediate feedback after each answer. In the passive learning group, participants reviewed their lecture notes. In the control group, participants watched the same lecture but did not engage in any review activities. Before signal recording, all participants received detailed written instructions advising them to avoid caffeine or alcohol for at least 12 hours prior, maintain a good night's sleep, and have a proper breakfast on the day of the experiment. EEG signals were recorded using a 32-channel AntiChamp system with electrodes positioned according to the international 10-20 system. Signals were sampled at 500 Hz, filtered between 0.5 and 50 Hz, and recorded at two points: before and immediately after the study session. Each session lasted approximately nine minutes and included four blocks: two eye-open blocks (2 minutes and 15 seconds each) and two eye-closed blocks (2 minutes and 15 seconds each).

3. METHODOLOGY

First, EEG data were preprocessed by applying a bandpass filter between 1-40 Hz and a 60 Hz notch filter to remove power-line noise, using the settings described in this paper [13]. The data were re-referenced to the average reference [14], and artifacts, including ocular movements, were removed using independent component analysis (ICA) with the same settings as in [15].

Then, the EEG signal was used to estimate functional connectivity between pairs of EEG channels with the phase lag index (PLI) [16], and the dFC was calculated as the Pearson's correlation between all pairs of FC matrices, as shown in figure 1. After preprocessing the EEG signals, phase estimation was performed using the Hilbert Transform [17]. The Hilbert transform was applied with a sliding-window method with 50% overlap, using windows of 250 milliseconds each. The continuous phase signals were segmented into non-overlapping epochs of 0.25 seconds, resulting in approximately N =1080 epochs for each EEG recording. For each epoch, functional connectivity between pairs of EEG channels was determined using PLI. PLI is based on the asymmetry of the distribution of phase differences between two signals, and is calculated according to:

$$PLI = \frac{1}{K}\left|\sum_{t}^{K} \text{sign}[\sin\,(\Delta\emptyset(t))]\right| \tag{1}$$

where K is the number of samples per epoch, and $\Delta\emptyset(t)$ is the phase difference between two signals at time t, in radians. The number of channels from 31 to 18 was reduced to maintain balanced coverage across all brain regions: 8 left, 8 right, and 2 midlines. So, a symmetric connectivity matrix of size 18 by 18 per epoch. A PLI value of 0 indicates no functional connectivity, whereas a value of 0 indicates maximal functional connectivity [10].

Since the FC matrices are symmetric, each 18×18 matrix was converted into a 153-element vector by extracting the upper triangle. Then, a 231-by-N matrix of time-varying FC across all brain regions is obtained, where N is the number of epochs. Next, dFC is computed by calculating Pearson's correlation coefficients for all pairs of FCs. A symmetric dFC matrix of size 153 by 153 is obtained for each EEG recording. Each element in the dFC matrix presents the correlation strength between two time-varying FC values. The dFC matrices are symmetric; each matrix is transformed into a 11628-long vector by extracting the upper triangle. This 11628-long dFC vector was used for statistical analysis, including a paired t-test for within-subject comparisons and a Welch's t-test for between-group differences. The results will be presented in the next section.

Then, the Euclidean distance measure [18] was used to calculate the distance between the dFC matrix before extracting the upper triangle. So, the 153 by 153 distance matrix was obtained. Multidimensional scaling (MDS) [19] reduces the data to 30 dimensions, and these MDS features are then used for machine learning classification. Two machine learning models, KNN and RF, were used to classify within-group and between-group differences. The 5-fold cross-validation was performed with hyperparameter tuning using HalvingGridSearchCV [20] for both KNN and RF model.

4. RESUTLS AND DISCUSSION

In the statistical analysis, the dFC vectors were used to examine within-group differences, comparing before and after within each learning group (control, active, and passive). For this analysis, a paired t-test was used to find the statistical significance of within-group differences. For the differences between groups, which are the group differences after active and passive learning strategies, as well as the control group. Welch's t-test was used for this analysis. Both within-group and between-group differences in dFC vectors were statistically significant, and the Bonferroni-corrected *p*-values are presented in table 1. The ANOVA was used to test for statistical differences among the control, active, and passive learning groups. The *p*-value is less than 10^{-8}, indicating that the dFC vectors show a statistically significant difference between the groups.

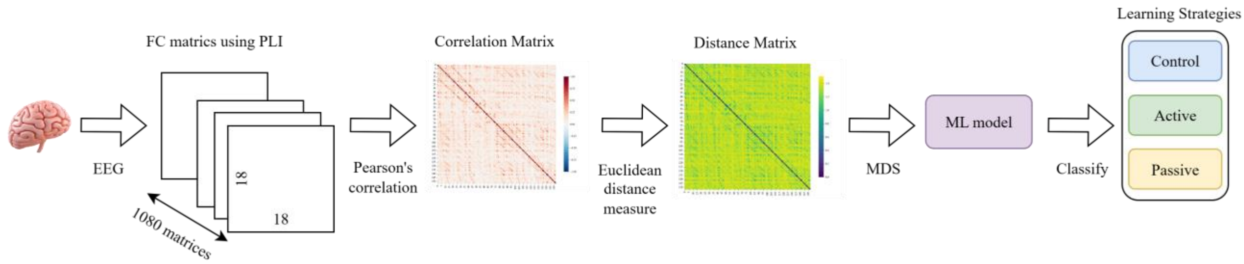

Fig 1: Overall framework for classification of different learning methods

Table 1. Statistical analysis of within-group differences and between-group differences

Within-group		*p*-value	Between-group		*p*-value
Pre vs Post	Control	$p<10^{-8}$	Post vs Post	Control vs Active	$p<10^{-8}$
	Active	$p<10^{-8}$		Control vs Passive	$p<10^{-8}$
	Passive	$p<10^{-8}$		Active vs Passive	$p<10^{-8}$

The MDS features were used to identify differences within and between groups using machine learning algorithms. For the control group, classification between the pre-control and post-control groups (combining eye-open and eye-closed data) with machine learning algorithms showed that KNN achieved an average of over 80% across all performance measures. However, RF achieved an average of over 65% across all performances. For the active and passive groups, the classification performance measures were over 83% and 82%, respectively. The results are presented in figure 2, and the bar plot represents each group. To test the learning strategies, analyze the differences between groups after the participants performed their respective learning strategies. Accuracy, precision, recall, and F1-score are defined as follows:

- Accuracy represents the proportion of correctly classified instances (positive and negative) out of the total number of instances. The formula is (TP + TN)/(TP + TN + FP + FN).
- Precision indicates the proportion of true positive predictions among all instances predicted as positive. Its formula is TP/(TP+FP).
- Recall denotes the proportion of actual positives that the model correctly identified. It is calculated as TP/(TP+FN).
- F1-score provides a metric that combines precision and recall by computing their harmonic mean: 2×(Precision × Recall)/(Precision + Recall).

In these formulas, TP stands for true positive, TN for true negative, FP for false positive, and FN for false negative.

Figure 3 shows the bar plot for each group's difference, with classification measures above 84% for KNN and over 70% for RF between the control and active learning groups. For the control versus passive learning groups, the performance measures of KNN and RF averaged 82% and 67%, respectively. Figure 4 shows the classification performance across control, active, and passive groups. The ML models can still distinguish the MDS features of these groups, achieving 77.53% accuracy with KNN and 60% with RF. Other performance metrics are also above 70% with KNN and 60% with RF. Therefore, there are significant pre-post and post-post changes in dFC resting-state EEG, both within and

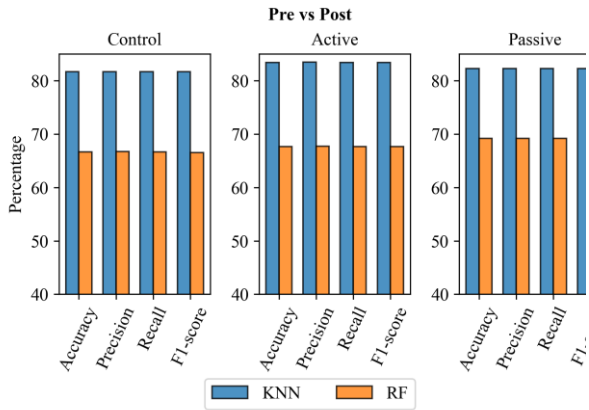

Fig 2: Bar plot showing classification performance values of within-group differences

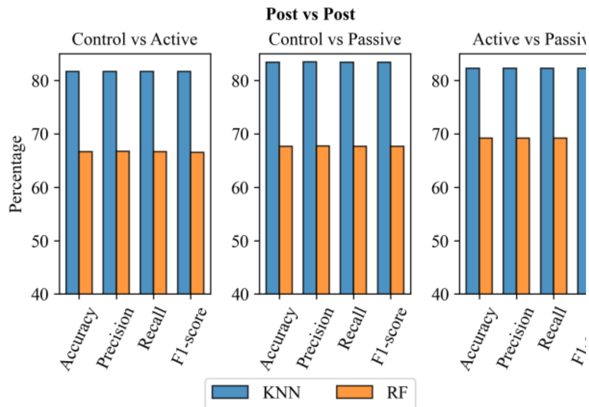

Fig 3: Bar plot showing classification performance for between-group differences

between groups. The different learning strategies are effective for the participants in each group, and the dFC also correlates with the neural changes in their brain regions. The results of this research, obtained through various statistical analyses and machine learning algorithms, support the statement above.

In this research, all brain regions were examined to compute the dFC matrices and analyze the changes in their MDS features between each group's pre- and post-effect states. There is no analysis across different EEG frequency bands, as the entire signal is used for this computation. Therefore, there is significant potential to explore how dFC changes relate to specific brain regions and frequency bands. Future research will focus on investigating differences across various frequency bands and comparing different brain regions, which may provide better insights into changes in dFC matrices.

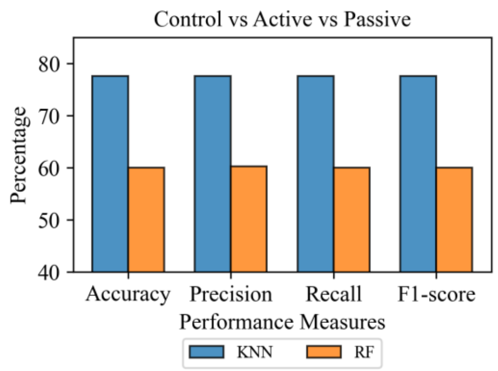

Fig 4: Classification performance across multiple groups

5. CONCLUSION

This work proposes a novel framework for examining the changes in dFC matrices from different study groups. The results support this finding and allow for investigation of brain functioning at both within- and between-group levels. Therefore, this research could lead to the discovery of a new biomarker for cognitive changes and even for neurodegenerative diseases. In this research, educational EEG is used to investigate which neural activities are correlated with different learning methods using dFC matrices and various machine learning models. Therefore, future work will focus on identifying new biomarkers for dFC matrices and MDS features to distinguish between normal conditions and neurodegenerative diseases.

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