



Functional Brain Network Analysis In Dyslexia Using Graph Theory Metrics

Ozlem Karabiber Cura
Dept. of Biomedical Engineering
Izmir Katip Celebi University
Izmir, TURKEY
ozlem.karabiber@ikcu.edu.tr

Sevde Dervisoglu
Dept. of Biomedical Engineering
Izmir Katip Celebi University
Izmir, TURKEY
dervisoglusevde@gmail.com

Günet Eroglu
Dept. of Computer Engineering
Bahçeşehir University
Istanbul, Turkey
gunet.eroglu@eng.bau.edu.tr

Abstract—This study investigated brain network changes in 14 children diagnosed with developmental dyslexia over a 60-day cognitive training period using EEG-based functional connectivity and graph theory analysis. Features such as CPSD, MSC, correlation coefficient, and entropy-based measures are extracted from EEG recordings. Subsequently, seven graph metrics (assortativity, transitivity, clustering coefficient, global efficiency, local efficiency, modularity, and characteristic path length) are calculated. The extracted features are classified using machine learning models. The analyses showed increased brain network integration and strengthened long-range connectivity by Day 60. These findings suggest that cognitive intervention may promote neuroplasticity in children with dyslexia and that EEG-based graph metrics could serve as potential biomarkers for monitoring treatment progress.

Index Terms—Developmental dyslexia, EEG, functional connectivity, graph theory, neuroplasticity, cognitive training, machine learning, CPSD, coherence, entropy, brain network metrics.

I. INTRODUCTION

Developmental dyslexia is a prevalent and heterogeneous neurodevelopmental disorder characterized by persistent difficulties with reading, decoding, and spelling, despite normal intelligence and adequate educational conditions [1]. The prevalence of dyslexia in society is not well understood by families or educators. According to the Turkish Dyslexia Association, 41,600 of Turkey's 85 million citizens have been diagnosed with dyslexia, which represents just 0.05% of the country's entire population, despite the fact that the illness is thought to affect at least 10% of people in every society [2]. Although traditionally viewed as a phonological processing disorder, growing evidence suggests that dyslexia stems from a more complex interplay of deficits in phonological awareness, working memory, attentional control, and executive functioning. These deficits indicate the involvement of multiple, distributed brain regions and network-level dysfunctions, rather than a single localized abnormality [3].

Teacher reports, observations, and standardized tests are used to diagnose dyslexia in youngsters. Frequent reading lag may be a sign of dyslexia; however, timing and criteria can differ, requiring further neuropsychological or medical testing [4]. Electroencephalography (EEG) has emerged as a power-

ful, non-invasive, and cost-effective tool for investigating the temporal dynamics of brain function in neurodevelopmental disorders. Owing to its excellent temporal resolution, EEG is particularly suited for capturing the fast-paced neural processes involved in language and reading. Potential implications for early dyslexic identification are suggested by Castillo-Barnes et al.'s work, which examines dyslexia in Spanish readers using cross-frequency coupling analysis and EEG signals [4]. Significant differences in fixation-related potential amplitudes between chronological age controls and dyslexics during serial Rapid-Automatized Naming (RAN) tasks are shown by an electroencephalography and eye tracking investigation, indicating a link between dyslexia and neurocognitive processes [5]. According to a study that uses EEG data to examine brain mechanisms in low-level auditory processing, dyslexic patients differ from control patients in their network features, including a loss of small-world topology [6]. Using a k-nearest neighbor classifier, a study of dyslexic children revealed a 96.7% classification accuracy, along with poor functional segregation and disrupted information transfer in their brain networks [7].

A. Objectives of the proposed study

The primary objective of this study is to investigate the neuroplastic effects of a 60-day cognitive training protocol on children diagnosed with developmental dyslexia using EEG-based functional connectivity and graph theoretical analysis. Specifically, the study aims to:

- 1) Quantify changes in functional brain connectivity over time by extracting both linear and nonlinear EEG-based connectivity measures (CPSD, MSC, Coef, Covv, RE_Coef, CE_Coef).
- 2) Evaluate alterations in large-scale brain network topology by computing seven graph theory metrics (assortativity, transitivity, clustering coefficient, global efficiency, local efficiency, modularity, and characteristic path length).
- 3) Classify pre- and post-training brain network states using supervised machine learning algorithms (Fine Tree, Logistic Regression, Fine KNN, Linear SVM, Bagged Trees) to identify patterns indicative of training-induced neuroplasticity.

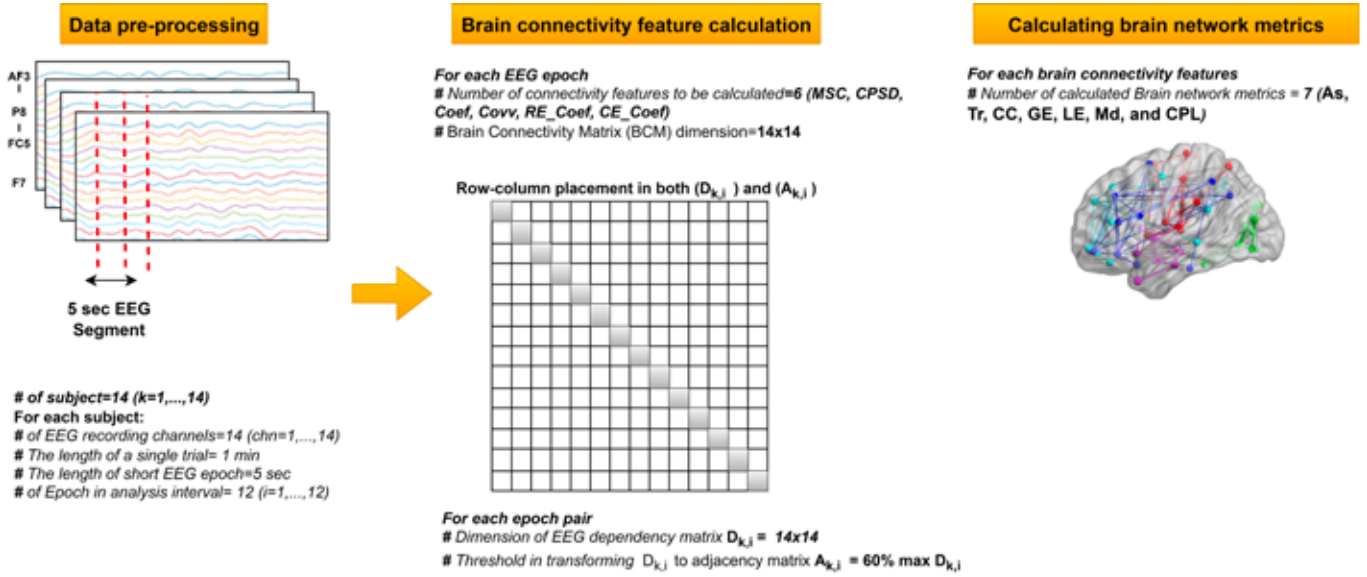


Fig. 1: The main steps of the EEG analysis procedure.

- 4) Assess the potential of EEG-derived graph metrics as biomarkers for monitoring the effectiveness of cognitive interventions in dyslexia.

Through this multi-modal approach, the study seeks to deepen the understanding of the neural basis of dyslexia and contribute to the development of objective, EEG-based tools for tracking treatment progress in educational and clinical settings.

II. MATERIALS AND METHODS

Figure 1 illustrates that EEG signals are recorded from 14 subjects across 14 channels, with each recording lasting 1 minute. These 1-minute recordings are analyzed by dividing them into 12 short periods (epochs) of 5 seconds. A 14x14 dependency matrix ($D_{k,i}$) is calculated for each epoch pair, and this matrix is converted to an adjacency matrix ($A_{k,i}$) by taking the threshold as 60% of the maximum value. This process is performed to compare brain connectivity before and after treatment using six different brain connectivity features.

A. Subjects and Experimental Data

EEG data are acquired from 14 children diagnosed with developmental dyslexia across two sessions: Day 1 (pre-training) and Day 60 (post-training). Each participant underwent a 1-minute EEG recording in a relaxed, eyes-open state, conducted in a quiet room with minimal external distractions. Data collection is performed using a 14-channel EEG system with electrode placement conforming to the international 10–20 system [8]. The electrode positions included AF3, AF4, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, and F8. Signals are recorded at a sampling rate of 500 Hz with an online band-pass filter of 0.5–45 Hz. The ground electrode is located at FPz, and the reference was placed on the left mastoid [2].

Preprocessing of EEG data is conducted using MATLAB R2024b and the EEGLAB toolbox. Raw EEG signals are band-pass filtered between 0.5 Hz and 45 Hz to eliminate slow drifts and high-frequency noise, preserving activity across the delta, theta, alpha, beta, and low gamma bands relevant to cognitive processing. Artifacts such as eye blinks and muscle activity were removed using Independent Component Analysis (ICA). The 1-minute continuous EEG data are then segmented into twelve non-overlapping epochs of 5 seconds each. Epochs with voltage fluctuations exceeding $\pm 100 \mu V$ are excluded. Baseline correction is applied to all valid epochs before further feature extraction and analysis.

B. Functional Connectivity Calculation

To capture inter-regional communication, six different pairwise connectivity measures are calculated between all 91 electrode pairs (computed from 14 electrodes) for each 5-second epoch. These measures included cross-power spectral, magnitude-squared coherence, Pearson correlation coefficient, covariance, correntropy coefficient, and coentropy coefficient. These features are selected to capture both linear (Coef, MSC, Covv) and nonlinear (RE_Coef, CE_Coef) dependencies among brain regions. Feature values are computed for each epoch.

C. Network Analysis Based on Graph Theory

In this study, graph theoretical analysis is applied to EEG-derived functional connectivity networks across Day 1 and Day 60. Functional connectivity matrices are constructed per subject and EEG epoch using multiple estimators. To ensure connected and meaningful network structures, proportional thresholding retaining 60% of the strongest connections (i.e., threshold range from 0.6 to 1.0) is applied. The thresholded adjacency matrix is represented as an undirected weighted

graph with 105 segments as nodes. Seven graph metrics are computed for each network: assortativity (As), transitivity (Tr), clustering coefficient (CC), global efficiency (GE), local efficiency (LE), modularity (Md), and characteristic path length (CPL). These metrics are calculated for each connectivity method, producing a feature set of 7 metrics $\times$ 6 connectivity features = 42 features. Lastly, these features are inputs to supervised classification models to evaluate temporal changes in network topology [8], [9].

D. Machine Learning Classification

In this study, supervised machine learning algorithms are applied to distinguish between Day 1 and Day 60 EEG data using a dataset consisting of 42 features. These included seven graph metrics calculated across six connectivity features. Fine KNN classification is used, with performance evaluated using 5-fold cross-validation. The performance of the classifier is assessed in this study using the following performance criteria: Accuracy (ACC), Sensitivity (SEN), Specificity (SPE), Positive Predictive Value (PPV), False Discovery Rate (FDR), and F1 Score (F1-S).

In addition to classification, circular connectivity graphs are created to visualize functional connectivity patterns. The brain is divided into 105 anatomical regions, and connections between these regions are mapped to illustrate changes in brain network organization after training. This combined approach allowed for both quantitative and visual interpretation of the neural changes over time.

III. RESULTS AND DISCUSSION

This study examined EEG-based functional connectivity and brain network changes in 14 children with developmental dyslexia before and after a 60-day cognitive training program. Linear and nonlinear connectivity measures are extracted from 14-channel EEG data, and graph theoretical metrics are computed to evaluate network topology. Using 42 features derived from six connectivity types and seven graph metrics, machine learning models classified Day 1 and Day 60 recordings with high performance. Circular connectivity graphs further visualized enhanced network integration and long-range connections post-training, suggesting cognitive intervention-induced neuroplasticity.

Table I summarizes the classification performance of the Fine KNN algorithm across six EEG-based connectivity measures (CE_Coef, Coef, Covv, CPSD, MSC, RE_Coef), averaged across 14 subjects in distinguishing between pre- and post-training sessions. Among the features, RE_Coef achieved the highest performance with 99.16% accuracy and an F1-S of 99.3%, followed by MSC and Coef with similarly strong results. In contrast, CPSD showed the lowest performance, with reduced specificity and the highest false discovery rate. Overall, the results highlight that nonlinear connectivity metrics, particularly RE_Coef, are more effective in capturing training-related neuroplastic changes in children with dyslexia when used with Fine KNN classification.

TABLE I: Classification results of the fine KNN model using six EEG connectivity features, evaluated with performance metrics.

Connectivity Features	ACC	SEN	SPE	PPV	FDR	F1-S
CPSD	88.41	89.79	84.99	91.19	8.81	90.36
MSC	98.43	99.10	97.22	98.39	1.61	98.72
Coef	98.13	99.59	95.89	97.51	2.49	98.52
Covv	91.86	92.54	90.26	94.25	5.75	93.34
CE_Coef	96.29	96.67	95.47	97.19	2.81	96.88
RE_Coef	99.16	99.08	99.34	99.53	0.47	99.30

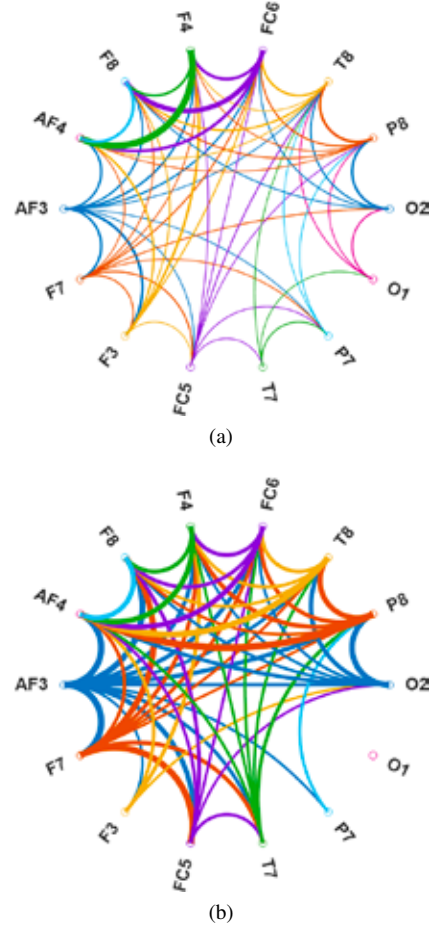


Fig. 2: Circular Connectivity Graph of RE_Coef for (a) Day 1 and (b) Day 60

Circular connectivity graphs of one epoch of one subject based on the RE_Coef metric, comparing functional brain networks at Day 1 and Day 60 of the cognitive training protocol, are given in Figure 2 to visualize functional connectivity patterns. Each node represents one of the 14 EEG electrode positions (AF3, AF4, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8), and the colored lines (edges) indicate functional connections derived from nonlinear RE_Coef values. The Day 1 graph shows sparser and more localized connectivity patterns, with fewer long-range connections between distant brain regions. In contrast, the Day 60 graph demonstrates a clear increase in both the number and distribution of inter-regional connections, particularly between frontal, temporal, and posterior, suggesting cognitive intervention-induced neuroplasticity.

and occipital lobes. This denser and more integrated network structure observed after training suggests improved global communication efficiency and reflects training-induced neuroplastic changes

The graph in Figure 3 examines the subject-based ACC and SEN distributions of different connectivity metrics (MSC, CPSD, Coef, Covv, RE_Coef, and CE_Coef). The MSC, RE_Coef, and CE_Coef metrics have high median values and narrow distributions across both performance measures, providing the most successful and consistent results. In contrast, CPSD and Covv have the widest distribution and low outliers, demonstrating the lowest consistency. Coef, on the other hand, exhibited a more limited success rate and a wider variance, demonstrating a moderate performance. These results demonstrate that the MSC, RE_Coef, and CE_Coef metrics are particularly reliable and stable.

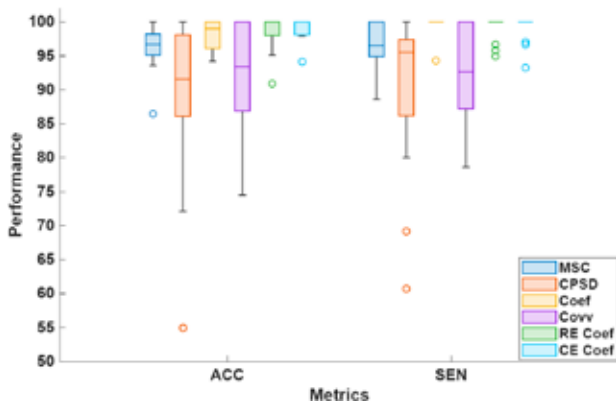


Fig. 3: Box plot of subject-based performance distribution for ACC and SEN values.

IV. CONCLUSION

This study demonstrates that a 60-day cognitive training program led to measurable changes in the brain network organization of children with developmental dyslexia, as assessed through EEG-based functional connectivity and graph theoretical analysis. The observed increases in global and local efficiency, clustering, and long-range connections—particularly evident in nonlinear metrics like RE_Coef—indicate enhanced network integration and suggest that targeted interventions can promote neuroplasticity. Machine learning models successfully classified pre- and post-training brain states, supporting the potential of EEG-derived graph metrics as objective biomarkers for monitoring cognitive treatment outcomes. Overall, the findings highlight the value of combining EEG, graph theory, and machine learning to understand and track functional brain changes in dyslexia.

It is particularly noteworthy that there is a significant increase in both the number and distribution of intraregional connections between the frontal, temporal, and occipital lobes. This denser and more integrated network structure observed after training suggests improved global communication efficiency and reflects training-induced neuroplastic changes.

The RE_Coef metric, which captures higher-order statistical dependencies, appears particularly sensitive to these functional reorganizations in the brains of dyslexic children.

ACKNOWLEDGMENT

Following an explanation of the experimental procedure by the research ethics committee, approval of the study protocol by the Yeditepe University Ethics Committee, and registration of the clinical trial with the Turkey Pharmaceuticals and Medical Devices Agency (TİTÇK) (Nbr: 71146310-511.06.2.11.2018), all participants gave their informed consent.

REFERENCES

- [1] R. L. Peterson and B. F. Pennington, "Developmental dyslexia," *The lancet*, vol. 379, no. 9830, pp. 1997–2007, 2012.
- [2] G. Eroglu, M. Köprülü, and B. Karabacak, "Dyslexia biomarker detection with qeeg data in children: Feasibility, acceptability, economic impact, pilot study and survey results," *Qeios*, pp. 1–19, 2022.
- [3] M. J. Snowling and C. Hulme, "Annual research review: The nature and classification of reading disorders—a commentary on proposals for dsm-5," *Journal of child psychology and psychiatry*, vol. 53, no. 5, pp. 593–607, 2012.
- [4] D. Castillo-Barnes, N. J. Gallego-Molina, M. A. Formoso, A. Ortiz, P. Figueiredo, and J. L. Luque, "Probabilistic and explainable modeling of phase-phase cross-frequency coupling patterns in eeg. application to dyslexia diagnosis," *Biocybernetics and Biomedical Engineering*, vol. 44, no. 4, pp. 814–823, 2024.
- [5] C. Christoforou, A. Fella, P. H. Leppänen, G. K. Georgiou, and T. C. Papadopoulos, "Fixation-related potentials in naming speed: A combined eeg and eye-tracking study on children with dyslexia," *Clinical Neurophysiology*, vol. 132, no. 11, pp. 2798–2807, 2021.
- [6] N. J. Gallego-Molina, A. Ortiz, F. J. Martínez-Murcia, M. A. Formoso, and A. Giménez, "Complex network modeling of eeg band coupling in dyslexia: An exploratory analysis of auditory processing and diagnosis," *Knowledge-based systems*, vol. 240, p. 108098, 2022.
- [7] N. G. Seshadri, B. K. Singh, and R. B. Pachori, "Eeg based functional brain network analysis and classification of dyslexic children during sustained attention task," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 4672–4682, 2023.
- [8] H. Chen, Y. Song, and X. Li, "A deep learning framework for identifying children with adhd using an eeg-based brain network," *Neurocomputing*, vol. 356, pp. 83–96, 2019.
- [9] S. Aydın, F. H. Cetin, M. Ç. Uytun, Z. Babadagi, A. S. Gueven, and Y. Işık, "Comparison of domain specific connectivity metrics for estimation brain network indices in boys with adhd-c," *Biomedical Signal Processing and Control*, vol. 76, p. 103626, 2022.