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AI-enabled Computational Intelligence Approach to Neurodevelopmental Disorders Detection Using rs-fMRI Data

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Abstract

Neurodevelopmental disorders (NDDs), including ADHD and ASD, profoundly impact children and adolescents. Leveraging Machine Learning (ML), Deep Learning (DeepL) on Functional magnetic resonance imaging (fMRI) data offers enhanced insights, advancing the understanding and diagnostic capabilities of NDDs. Traditionally, researchers extract time series data from predefined brain regions (ROIs) using atlas-based methods and focus on generating brain functional connectivity using Pearson correlation by analyzing changes in signal amplitude over time. This conventional approach assumes that the brain's structure can be modeled in a simple Euclidean space and predicted with conventional ML/DeepL techniques. However, these traditional methods have several drawbacks. Predefined ROI extraction fails to capture the inherent variability in brain connectivity patterns across individuals, potentially missing crucial information, while relying on Pearson correlation to analyze functional brain connectivity is sensitive to amplitude fluctuations caused by high neural oscillations, leading to inaccurate representations of true neural relationships. Modeling brain functional structure in Euclidean space does not account for the brain's complex, non-linear neural dynamics, limiting the effectiveness of ML/DeepL models. To address these issues, we propose: 1) An approach that adapts ROIs for each subject using combined grouped Independent Component Analysis (ICA) and Dictionary Learning (DL), better representing individual brain topologies; 2) The application of Phase Locking Value (PLV) to estimate functional connectivity in the frequency domain, reducing sensitivity to amplitude variations while effectively capturing both linear and non-linear signal relationships; 3) The implementation of a Graph Convolutional Network (GCN) to address the brain's non-Euclidean topological structure with graph architecture, enhancing the classification and diagnosis of neural disorders. This method was tested on the ADHD-200 dataset for ADHD and the ABIDE-I dataset for ASD, achieving high accuracy (94% ±1.3% for ADHD and 89.3% ±2.3% for ASD) through 10-fold cross-validation. The integration of data-driven ROI extraction, frequency-domain connectivity analysis, and non-Euclidean graph-based brain architecture representation collectively represents a novel approach to improving the understanding and prediction of NDDs.

Introduction