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# Machine Learning Approach to Detect and Analyze Attention-Deficit/Hyperactivity Disorder

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**_Abstract_**

*Attention-Deficit/Hyperactivity Disorder (ADHD) is a neurodevelopmental disorder characterized by difficulties with attention, impulse control, behavioral regulation, and daily functioning that persist across childhood and adulthood. Clinical diagnosis is predominantly based on behavioral assessments and expert interpretation, which may result in subjectivity and delayed clinical decisions. To reduce reliance on subjective evaluation, this study introduces an automated ADHD identification framework that integrates resting-state functional Magnetic Resonance Imaging (rs-fMRI) with advanced machine learning models. Functional connectivity features are derived using a seed-based strategy that quantifies voxel-level correlation patterns between selected brain regions and the rest of the brain. The analysis emphasizes the Default Mode Network (DMN), given its established involvement in attention regulation and executive processing. A Convolutional Neural Network (CNN) is employed to perform classification, leveraging its capacity to learn spatially complex representations from high-dimensional neuroimaging data. The proposed framework is evaluated on the ADHD-200 Global Competition dataset, consisting of rs-fMRI scans from 776 participants acquired across multiple sites. The findings indicate that the proposed model outperforms traditional machine learning methods in terms of classification performance.*

**Keywords:** Attention-deficit/hyperactivity disorder, rs-fMRI, deep learning, CNN, functional connectivity, default mode network

## INTRODUCTION

Attention-Deficit/Hyperactivity Disorder (ADHD) is a long-term neurodevelopmental condition marked by ongoing difficulties with attention, impulse control, and the regulation of activity levels. The condition affects individuals worldwide and is frequently associated with long-term educational, occupational, and social difficulties. Despite its prevalence, accurate diagnosis remains challenging due to heterogeneous symptom presentation and overlapping with other neuropsychiatric conditions [1, 2].

Recent developments in neuroimaging and computational modeling have significantly advanced the objective investigation of brain function, enabling researchers to study neurological and psychiatric disorders beyond traditional behavioral and clinical observations. Among the various neuroimaging modalities, resting-state functional Magnetic Resonance Imaging (rs-fMRI) has emerged as a powerful non-invasive technique for examining intrinsic brain activity. Unlike task-based fMRI, rs-fMRI captures spontaneous neural activity while the subject remains at rest by measuring low-frequency fluctuations in blood oxygen level–dependent (BOLD) signals [3, 4]. These fluctuations reflect synchronized activity between spatially distinct brain regions, allowing the assessment of functional connectivity across large-scale brain networks. The resulting connectivity

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patterns provide quantitative biomarkers that reveal alterations in brain organization associated with various neurological and psychiatric conditions. By transforming these connectivity measures into computational features, machine learning algorithms can identify complex and subtle patterns that may not be apparent through conventional statistical analyses. Consequently, these approaches have shown considerable potential for differentiating clinical populations from healthy controls, supporting early diagnosis, improving classification accuracy, and contributing to the development of objective, data-driven clinical decision support systems [5, 6].

A growing body of research has investigated the automatic classification of Attention-Deficit/Hyperactivity Disorder (ADHD) using a variety of neurophysiological and neuroimaging modalities, including electroencephalography (EEG), motion-based behavioral measurements, structural Magnetic Resonance Imaging (sMRI), and resting-state functional Magnetic Resonance Imaging (rs-fMRI). Early studies primarily employed conventional machine learning algorithms, such as Support Vector Machines (SVMs), Decision Trees, Random Forests, and k-Nearest Neighbors (k-NN), using handcrafted features extracted from imaging or physiological data. Although these approaches demonstrated moderate classification performance, their effectiveness largely depended on the quality of manually engineered features and their ability to capture complex nonlinear relationships within high-dimensional brain data [7, 8]. More recently, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have gained considerable attention because of their capability to automatically learn hierarchical feature representations directly from neuroimaging data. These models have shown improved classification accuracy and greater potential for identifying subtle patterns associated with ADHD. Despite these advancements, several important challenges remain unresolved. Models often exhibit limited generalization across imaging sites due to variations in scanner hardware, acquisition protocols, and demographic differences among study populations. Additionally, neuroimaging data are inherently noisy and high-dimensional, making deep learning models susceptible to overfitting when trained on relatively small datasets. Another significant limitation is the lack of biological interpretability, as many deep learning models function as “black boxes,” providing limited insight into the underlying neural mechanisms contributing to their predictions. To address these challenges, the present work integrates biologically meaningful functional connectivity features derived from rs-fMRI with a CNN-based deep learning framework. By leveraging connectivity patterns that reflect interactions among brain regions, the proposed approach aims to improve classification robustness, enhance generalization, reduce sensitivity to noise, and provide a more biologically informed framework for automated ADHD detection [9, 10].

## RELATED WORK

Machine learning-based analysis of neuroimaging data has been widely applied to ADHD classification. Seed-based functional connectivity approaches have been particularly useful for identifying disruptions in attention-related brain networks. Although these methods can capture pairwise relationships between regions, they often fail to represent higher-order spatial dependencies across the brain.

Deep learning models, especially Convolutional Neural Networks, have demonstrated strong performance in analyzing high-dimensional neuroimaging data by automatically learning hierarchical spatial features. Several studies have reported improved classification accuracy when CNNs are applied to fMRI-derived representations. More recent hybrid strategies that integrate functional connectivity measures with deep neural networks – particularly those focusing on clinically relevant networks such as the Default Mode Network – have yielded further improvements. Nevertheless, achieving an optimal balance between biological interpretability and deep feature learning remains an open research problem.

## PROPOSED METHODOLOGY

The proposed ADHD detection framework consists of four sequential components: rs-fMRI preprocessing, extraction of functional connectivity features, classification using multiple machine learning models, and quantitative performance evaluation.

 

**Data Preprocessing**

All rs-fMRI scans are processed using the Configurable Pipeline for the Analysis of Connectomes (C-PAC). The preprocessing pipeline is designed to improve the quality, consistency, and reliability of the rs-fMRI data before feature extraction and model training [11, 12]. It includes several essential steps, such as slice-timing correction to compensate for differences in image acquisition time across slices, head motion correction to minimize artifacts caused by subject movement during scanning, and skull extraction to remove non-brain tissues from the images. Spatial smoothing is applied to enhance the signal-to-noise ratio, while temporal filtering removes unwanted low- and high-frequency fluctuations unrelated to neural activity. Intensity normalization standardizes voxel intensity values across subjects, and image registration aligns each scan to a standardized brain template, enabling meaningful comparisons across individuals. To further reduce data dimensionality and ensure anatomical consistency, atlas-based brain parcellation divides the brain into predefined regions of interest (ROIs), from which representative signals are extracted. Finally, Principal Component Analysis (PCA) is employed to retain the most informative features while reducing redundancy, improving computational efficiency, and enhancing the performance and generalization capability of the subsequent machine learning and deep learning models [13, 14].

**Classification Models**

- *Convolutional Neural Network (CNN):* The CNN architecture accepts three-dimensional input volumes of size 224 × 224 × 64. It comprises multiple convolutional layers with Rectified Linear Unit (ReLU) activations to capture spatial patterns, followed by max-pooling layers for dimensionality reduction. Fully connected layers integrate learned features, and a softmax layer produces final class probabilities.
- *Support Vector Machine (SVM):* The SVM classifier is trained using reduced-dimensional feature vectors extracted from functional connectivity data. The model identifies an optimal separating hyperplane by maximizing the margin between ADHD and control samples.
- *Random Forest (RF):* The Random Forest classifier is an ensemble learning algorithm that consists of multiple decision trees, each trained on a different randomly sampled subset of the training data and a randomly selected subset of input features. This randomness introduces diversity among the individual trees, reducing the correlation between their predictions and improving the overall generalization performance of the model. During the prediction phase, each decision tree independently classifies the input instance, and the final output is determined through majority voting for classification tasks. By aggregating the predictions of multiple trees, the Random Forest classifier enhances robustness, reduces variance, mitigates the risk of overfitting, and generally achieves higher predictive accuracy compared to a single decision tree [15, 16].

## EXPERIMENTAL SETUP AND EVALUATION METRICS

Experimental evaluation is conducted using the ADHD-200 Global Competition dataset, which includes rs-fMRI scans from 776 subjects collected across multiple imaging sites. The dataset is split into training (80%) and testing (20%) subsets, and ten-fold cross-validation is used to ensure reliable and unbiased performance estimation. Model performance is assessed using accuracy, precision, recall, and F1-score metrics. Learning curves are examined to evaluate convergence and generalization behavior [17–19].

## RESULTS AND DISCUSSION

The CNN-based classifier achieved the highest performance, obtaining an accuracy of 97% with consistently balanced precision, recall, and F1-score values. The SVM demonstrated moderate performance, while the Random Forest classifier performed poorly when applied to high-dimensional fMRI-derived features.

The superior performance of the CNN model is attributed to its ability to learn complex hierarchical spatial representations from functional connectivity data, particularly within clinically relevant networks such as the Default Mode Network. These findings are consistent with recent advances in neuroimaging-based ADHD classification and highlight the effectiveness of deep learning for objective clinical decision support (Table 1).

**Table 1.** Comparative performance of ADHD classification models.

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| CNN | 97.0 | 96.8 | 97.2 | 97.0 |
| SVM | 83.0 | 81.5 | 78.9 | 80.1 |
| Random Forest | 50.0 | 49.8 | 50.3 | 50.0 |

## CONCLUSION AND FUTURE WORK

This study presents a fully automated framework for ADHD detection that integrates resting-state fMRI analysis with deep learning. By combining seed-based functional connectivity features with CNN architecture, the proposed method achieves high classification accuracy and outperforms traditional machine learning approaches.

Future work will focus on enhancing model transparency, addressing data imbalance, and validating the framework on independent datasets. Additionally, integrating multimodal data sources – such as EEG recordings and behavioral measures – may further improve diagnostic reliability and clinical applicability.

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