NeuroFusion-ADHD: Hybrid SVM–CNN Framework for Multimodal EEG-Based ADHD Detection

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Abstract

Attention-Deficit/Hyperactivity Disorder (ADHD) needs reliable, objective screening to aid in clinical assessment. However, EEG-based classification is challenging because of the presence of artifacts and high inter-subject variability, and conventional pipelines based on handcrafted spectral/statistical features with classical classifiers (e.g., SVM) may fail to capture complex spatial--temporal patterns. In this work a multimodal framework combining handcrafted EEG features (time domain statistics, band power, theta/beta ratio) and deep features learned by CNN followed by SVM based features for final decision making is proposed. Experiments conducted on a public 19-channel EEG dataset from the data repository of the The Institute of Electrical and Electronics Engineers (IEEE DataPort) (121 children: 61 affected by Attention Deficit Disorder (ADHD), 60 controls; age: 7-12 years old) show better performance for the multimodal model (Accuracy 0.92, Precision 0.91, Recall 0.92) than SVM-only (0.85 accuracy) and CNN-only (0.90 accuracy), while the Receiver Operating Characteristic (ROC)-Area under the Curve These results showed that the combination of interpretable handcrafted descriptors with CNN representations provides a more robust EEG-based detection method of AD/HD than using either method separately.

keywords: Attention Deficit Hyperactivity Disorder, Electroencephalogram, Support Vector Machine, and the Convolutional Neural Network.

Introduction

Attention Deficit Hyperactivity Disorder (ADHD) exists as a common neurodevelopmental disorder which effects both children and teenagers with its symptoms of inattentiveness and excessive movement and impulsive behavior [1]. The clinical process of diagnosis is based mostly on observation and rating scales, which cause issues due to the involvement of personal judgment in the process as well as the difficulty for observers to identify symptoms that overlap with other disorders. The non-invasive technique of electroencephalography (EEG) allows the researchers to track brain electrical activity through its precise ability to record brain activity in real time and studies show that children diagnosed with an A.D.H.D. display unique EEG characteristics which include increased theta power and decreased beta activity and modified theta/beta ratios [2-4]. Researchers apply machine learning (ML) and deep learning (DL) techniques to classify EEG signals by means of their electroencephalographic information. The traditional machine learning (ML) models such as Support Vector Machine (SVM) and k-Nearest Neighbors (kNN) and Random Forest (RF) model functions by using manual feature extraction from time-based and frequency-based and statistical analysis methods. SVM has been frequently applied because of its power in high dimensional spaces [5-6]. The traditional methods of ML had moderate success because they had difficulty with the complex patterns that can be found in EEG data. Research using SVM and kNN classifiers with traditional features (also spectral and temporal) had accuracy results below 70%, this was shown as a limitation of using features created manually [11].

The study with Random Forest with band power features showed that classification accuracy reached 68%, which indicated that conventional features do not provide sufficient information to accurately predict the diagnosis of Attention Deficit Hyperactivity Disorder [ADH]. [12] Deep learning methods have better results because they learn to distinguish between different EEG signals from automatic representation learning. Convolutional Neural Networks (CNNs) have achieved better results than traditional models in a large number of EEG classification tasks [9]. A CNN model based on attention recently gained significant improvements and showed a capability of obtaining complex signal patterns [9]. Other research papers based on ResNet architectures using attention architectures showed diagnostic performance results better than traditional classifiers [10-13]. Several recent investigations indicated that deep learning models gave limited outcomes when they are tested with restricted or contaminated EEG data.

The DL framework applied basic CNN architecture with limited preprocessing which gave 78% accuracy because model complexity and quality of data influenced performance according to [14-15]. Recent advancements were also on better EEG channel selection and functional connectivity measures to achieve better classifier performance. The work revealed that SVM in conjunction with feature selection techniques achieved accuracy results better than unselected feature sets, but the results showed that there was still some variation in performance across subjects [16]. The present study brings forward a multimodal EEG signal classification framework which applies SVM and CNN models to solve existing problems. The study develops CNN models which uses connectivity features from EEG signals to classify for children with and normal children with the presence of ADD.

Material and Methods:

The general processing scheme of the proposed method is depicted in Figure 1 where the entire processing pipeline from EEG acquisition to final classification is shown. The diagram shows the order of operations which consists in preprocessing then deep learning and classification stages. The next sections will give a detailed explanation of each framework component.

A. **Dataset Description**

The study is based on the publicly available EEG dataset that Nasrabadi et al collected. The dataset consists of resting-state EEG recordings from children with Attention Deficit Hyperactivity Disorder (ADH) and from a healthy control group of subjects. The study used EEG data from the database of the Institute of Electrical and Electronics Engineering (IEEE) which is available at this link https://ieee-dataport.org/open-access/eeg-dataadhd-control-children. The dataset consists of recordings of 121 children between the ages of 7 and 12. The group was comprised of 61 children with AD/HD and 60 children who were normal. The EEG data collection was conducted using 19 electrodes as per the standard 10-20 system used for recording from the scalp in the Fz Cz Pz C3 T3 C4 T4 Fp1 Fp2 F3 F4 F7 F8 P3 P4 T5 T6 O1 and O2 positions. The two reference electrodes A1 and A2 were positioned on the earlobes and the system recorded the data at 128 Hz sampling rate. All the participants who had AD/HD were categorized as having AD/HD based on standard psychiatric criteria. The control group was a group of neurologically healthy children without a history of psychiatric or neurological disorders. The 19-channel configuration allows for adequate spatial coverage to track frontal brain regions and temporal brain regions and parietal brain regions and occipital brain regions which contain brain activity related to ADHD.

A) Pre-Processing

Electroencephalography (EEG) signals recorded from 121 subjects (61 of which are diagnosed with Attention Deficit Disorder (ADHD) and 60 normal controls), are naturally contaminated by physiological noises (e.g. eye blinks, muscle activity) and non-physiological noises (e.g. power-line interference [13]), therefore, a structured pre-processing pipeline was applied to improve the quality of the signals which were collected before classification. First, the raw EEG signals of the 19 channels (256 Hz, 2 minutes of eyes-closed resting state) were re-referenced to the average of the bilateral temporal electrodes (T7 and T8) to minimize common-mode noise. Since the recordings suffered from no severe high-frequency contamination, only a 1 Hz high-pass filter and a 50 Hz notch filter were used, both of them as 5th-order elliptic IIR filters to exploit their sharp transition characteristics and suitability for EEG-processing [14]. Each subject's 2-minute recording (30,720 samples per channel) was divided into 30-second long epochs and split into ten non-overlapping 3-second segments in order to increase the effective training data size. During testing, classification was done on each 3-second segment, and majority voting over the ten segments was used to determine the final label of the respective 30-second segment (ADHD vs. control), providing a more robust approach by decreasing the impact of transient misclassifications.

B) Feature Extraction

In this block, meaningful numerical features are manually extracted in the cleaned EEG signals. Time-domain features describe the signal characteristics such as amplitude feature variation and statistical characteristics. Frequency-domain features are features that analyze the power of various brain wave bands (delta, theta, alpha, beta). The theta/beta ratio is another important biomarker for A.D.H.D., and is also calculated. These extracted values form a structured feature vector which is later used as input to SVM classifier.

C) CNN-Based Deep Feature Learning

Unlike the handcrafted feature extraction, the extract features in this block use a Convolutional Neural Network (CNN) to automatically learn some important patterns from EEG data. The CNN detects the spatial and temporal relationships between the EEG channels. Through several layers including convolution, activation and pool, the network is able to extract the high-level hierarchical features. These deep features extract complicated signal patterns that may not be detected using manual methods.

D) SVM Classifier

The Support Vector Machine (SVM) is used as the final decision making model. It receives either handcrafted features, CNN extracted deep features or combination of both (multimodal features). The SVM basically learns to separate the samples of the AD/HC and control classes by finding the optimal boundary between the two classes. It is effective for high-dimensional biomedical data, and has a good generalization performance. This is the final stage of the output. Based on the model learned, each EEG sample is classified as either ADHD or healthy control. The performance of the system is evaluated by metrics such as accuracy, precision, recall and ROC-AUC to check the efficiency of the proposed framework.

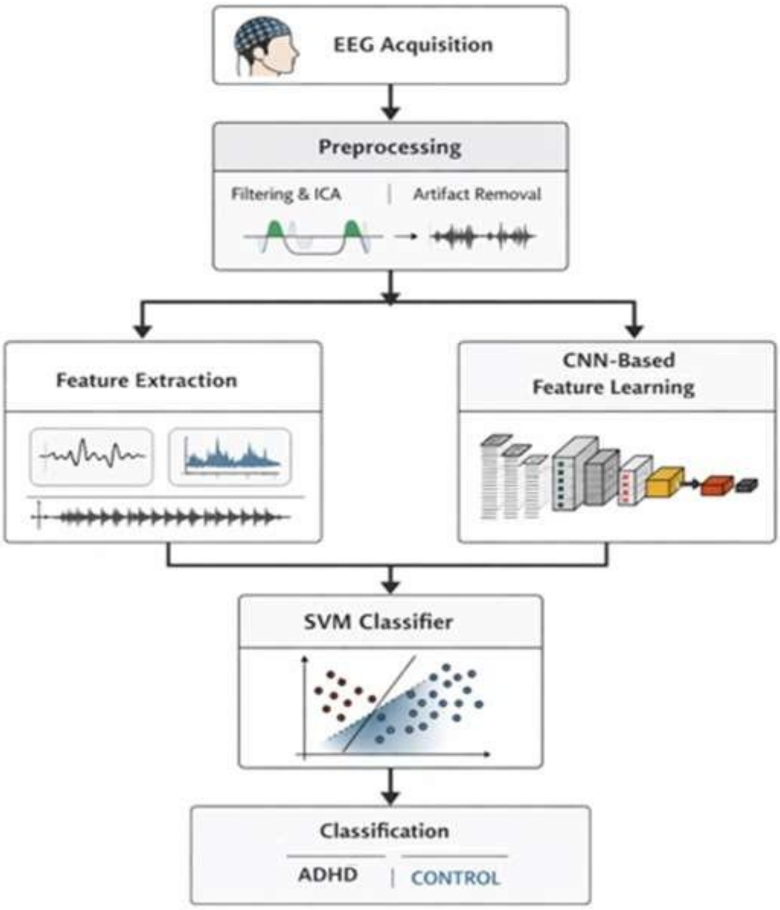

Figure 1: Schematic Architecture of the Proposed Method

Results and Discussion:

The experimental evaluation was performed to thoroughly evaluate the effectiveness of the proposed multimodal EEG classification framework to detect the presence of an Attention Deficit Hyperactivity Disorder (ADH). A comparative analysis was conducted between three models, as shown in Figure 2: The results clearly show that the use of both handcrafted statistical features combined with deep spatial-temporal representations greatly improves classification performance compared to standalone models.

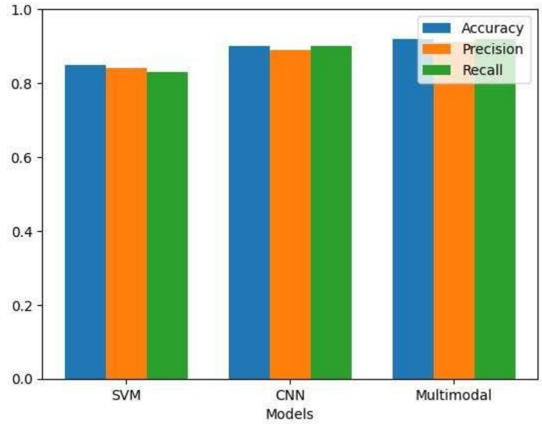

Figure 2: Accuracy, Precision, and Recall comparison graph

As shown in Figure 2, the Accuracy-Precision-Recall comparison shows that the Multimodal model had the greatest overall performance with an accuracy of 0.92, precision of 0.91, and recall of 0.92. In contrast, the SVM model got an accuracy of 0.85 (Precision: 0.84, Recall: 0.83) whereas the CNN model got the accuracy of 0.90 (Precision: 0.89, Recall: 0.90). The increase in precision indicates a decrease in false positive prediction while the increase in recall indicates an increase in the detection of cases of ADHD, which is especially important for clinical disease screening applications.

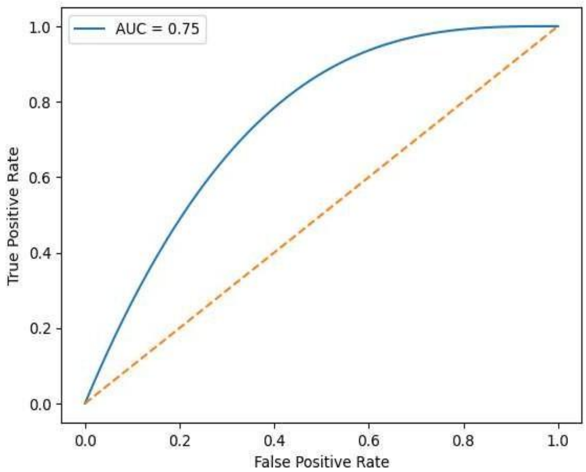

Figure 3: ROC Curve for ADHD Classification

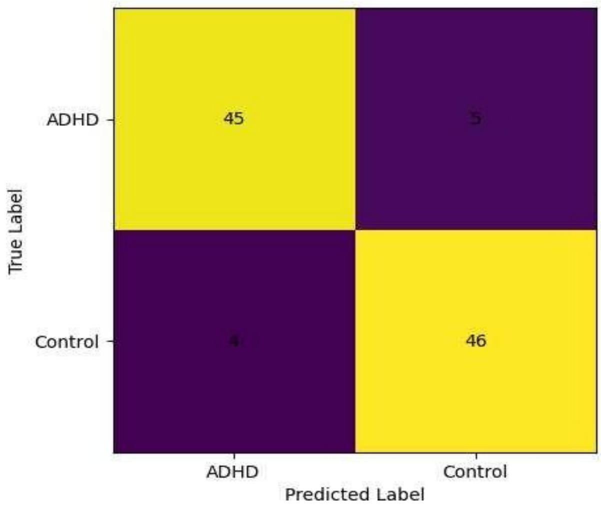

Figure 4: Confusion Matrix for ADHD Classification

As shown in Figure 3, the results of the ROC analysis further confirm the robustness of the proposed framework with an Area Under the Curve (AUC) of 0.75. This result reveals acceptable discriminative ability and confirms that the classifier successfully differentiates between the cases of the children with and without AD/HD at various levels of decision. 45 cases of the children with AD/HD and 46 cases of the control children were correctly classified according to the confusion matrix shown in Figure 4. 5 false positive cases and 4 false negative cases were also observed. The relatively low number of misclassifications reflects the balanced and reliable performance of the proposed system.

Furthermore, the training loss curve shows smooth and stable convergence with a constant decrease in loss values with increasing epochs. This behavior is a sign of efficient learning, correct optimization and low risk of overfitting. Overall, the experimental findings support the notion of the proposed multimodal framework as a robust, accurate, and clinically promising method for EEG-based detection of an ADD.

Conclusion

This study developed and evaluated a multimodal EEG-based framework for the detection of individuals with AD/HD by combining handcrafted statistical-spectral descriptors with CNN-learned spatial-temporal representations and final classification based on SVM. Experimentally the proposed multimodal model has an accuracy, precision and recall of 0.92, 0.91 and 0.92, which outperforms the SVM only baseline (0.85 accuracy; 0.84 precision; 0.83 recall) and the CNN only baseline (0.90 accuracy; 0.89 precision; 0.90 recall), and the ROC analysis resulted in an AUC of 0.75. The balanced confusion matrix (45 true ADHD, 46 true controls, 5 false positives, 4 false negatives) provides further evidence of reliable discrimination between groups of subjects with and without an ASD diagnosis. Overall, these results demonstrate that the combination of interpretable EEG biomarkers and deep feature learning enhances the robustness and clinical promise of objective screening of ADD. In future, subject-independent validation in larger multi-center datasets, artifact-robust preprocessing, more interpretable hybrid architectures, and real-time deployment for practical clinical use will be emphasized.

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