B.Tech Project Report

On

EEG classification Using Deep Learning Models

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Abstract

With the growing interest in brain-computer interfaces and mental health diagnostics, EEG-based analysis is becoming increasingly important. This project focuses on classifying EEG signals to help identify patterns associated with conditions like ADHD. We used a publicly available EEG dataset from Kaggle [1], where the recordings were collected from multiple subjects. To process the data effectively, we applied signal filtering techniques and divided the recordings into short, fixed-length segments. The architecture we used for classification was a variant of EEGNet, a deep learning model specifically designed for EEG data, enhanced with dropout and L2 regularization to reduce overfitting. We trained the model using data from different subjects, ensuring that training and testing sets were strictly separated at the subject level to avoid information leakage. Standard techniques like early stopping and learning rate adjustment were used to optimize the training process. The model was evaluated based on classification accuracy, and it achieved a final test accuracy of 81%. These results suggest that deep learning, when combined with proper EEG preprocessing, can be a powerful tool for classifying brain activity and potentially supporting clinical decisions in the future.

Keywords: EEG, ADHD, EEGNet, deep learning, brain-computer interface, neural networks, mental health classification

1. Introduction

In recent years, the use of EEG (electroencephalogram) signals has gained considerable attention in neuroscience and healthcare, especially in the context of diagnosing and understanding neurological disorders such as Attention Deficit Hyperactivity Disorder (ADHD). EEG is a non-invasive method for recording brain activity, offering valuable insights into neural functioning. Despite its potential, EEG data is complex; often noisy, high-dimensional, and highly variable between individuals, making analysis a significant challenge.

Traditional approaches, such as manual inspection or basic statistical methods, often fall short when it comes to detecting the subtle and complex patterns associated with mental health conditions. This has led to a growing interest in leveraging deep learning, which excels at automatically learning meaningful patterns from raw data. Among various architectures, models like Convolutional Neural Networks (CNNs) and EEGNet - a lightweight neural network tailored for EEG analysis - have shown promising results in EEG-based classification tasks.

Our project builds on this foundation by focusing on EEG-based detection of ADHD using a regularized version of EEGNet. We enhanced the model with dropout and L2 regularization to reduce overfitting and improve generalization. EEG signals were preprocessed using filtering and segmentation techniques, ensuring the input data was clean and structured for training.

A key part of our approach involved two evaluation strategies: **subject-dependent** and **subject-independent** testing. In the subject-dependent setup, the model is trained and tested on data from the same individuals, which can highlight how well it picks up personalized brain patterns. In contrast, the subject-independent evaluation ensures that the model is tested on completely unseen subjects - this more realistic scenario helps assess the model's ability to generalize to new users, which is crucial for real-world deployment.

Through this project, we aim to demonstrate how a carefully designed deep learning pipeline can support EEG-based diagnosis, helping advance mental health diagnostics and contributing to the broader field of brain-computer interfaces.

Contributions

- Developed a regularized version of EEGNet for multi-class EEG classification.
- Preprocessed EEG data using MNE, including filtering and epoch segmentation.
- Implemented subject-wise data splitting to evaluate model generalization.
- Analyzed performance using classification metrics and training curves.
- Proposed a scalable and robust deep learning framework for EEG diagnostics.

2. Related Work

The field of EEG-based classification has witnessed considerable advancements in recent years, driven by the need for more accurate and automated diagnostic tools for neurological and psychological conditions. Numerous studies have employed machine learning and deep learning approaches to interpret EEG signals, leveraging various datasets, preprocessing techniques, and model architectures to improve classification performance.

AUTHOR	Dataset	YEAR	Features	Model	Accuracy	Research Gaps
Werthman er al. [2]	High-density EEG data from Carnegie Mellon University	2019	Focus on identifying the most informative EEG channels (e.g., TPP8h, M1, PPO2h, FC6, P6), channel-wise analysis, frequency bands (4 Hz, 6 Hz)	XGBoost	91.77%	Needs better accuracy and ADHD subtype differentiation
He Chen, Yan Song, Xiaoli Li et al. [3]	EEG data from 50 children with ADHD and 51 matched controls	2019	Deep features from CNN; 13 hand-crafted brain network measures (degree, path length, efficiency, modularity, clustering, etc.)	CNN (4 architectures compared), MLP, SVM	CNN: up to **94.67%** on test set a; MLP: 84.75%; SVM: 84.17%	1. Small dataset size limits generalization. 2. ADHD subtypes not analyzed. 3. CNN acts as a black box — deep features lack explicit neurophysiological interpretability. 4. Needs validation with larger,

						diverse datasets.
Ekhlasi et al.[4]	ADHD EEG dataset (children)	2024	Multivariate transfer entropy, delay-optimized causal analysis, EEG channel interaction graphs	MuTESPO (Multivariate Transfer Entropy with Self-Prediction Optimization)	89.10%	Needs better multivariate, delay-aware connectivity modeling for ADHD subtype analysis
Akhi et al. [5]	EEG signals from children (Bangladesh)	2024	Euclidean distance features	Conv1D-GRU Hybrid Model	85%	Exploration needed for multimodal integration and more advanced model architectures
Zarina , Kareema et all[5]	ADHD-200 (INDI)	2025	Feature extraction transforms raw data into robust, informative features using models like autoencoders or dilated convolutions	Deep Autoencoder (DAE) and Dilated Casual Convolutional Network (DCL).	83.3%	Need for broader dataset validation, enhanced model interpretability, and improved real-world clinical

						applicability

3. Methodology

The section describes the methodology adopted in this study, detailing how the EEG data was prepared, the steps followed for signal preprocessing, and the classification models implemented. It includes both traditional machine learning and deep learning pipelines for EEG signal analysis.

3.1 Data Collection

The EEG data used in this project was obtained from a pre-existing CSV file named *adhdata.csv*. Each row in the dataset represents a single time point, while each column corresponds either to a specific EEG channel or to associated metadata such as the subject identifier and class label. The recordings were made using 19 EEG channels at a sampling rate of 128 Hz. The dataset was structured as a binary classification task, with each subject labeled as either belonging to the ADHD or control group.

3.2 Signal Preprocessing

To enhance signal quality and model performance, a series of preprocessing steps were conducted using the MNE-Python toolkit:

- Channel Selection & Referencing: Only EEG channels were retained for analysis. The signals were re-referenced to the common average to reduce bias from individual electrodes.

- Bandpass Filtering: A bandpass filter between 1 and 40 Hz was applied to eliminate low-frequency drifts and high-frequency noise.

- Epoching: The continuous EEG recordings were segmented into non-overlapping 2-second epochs (i.e., 256 time points per epoch).

- Artifact Removal with ICA: Independent Component Analysis was used to identify and remove noise artifacts. Components exhibiting extreme kurtosis (top 5%) were discarded, as they were likely to represent artifacts such as eye blinks or muscle movement.

- Label Assignment: Each epoch was labeled with the subject's corresponding class and ID, enabling subject-wise cross-validation during training.

3.3 Feature Engineering

Two distinct feature sets were derived depending on the classification model:

- Raw Epochs for Deep Learning: For convolutional neural networks, the preprocessed EEG segments were normalized and reshaped to a 3D format: (channels, time points, 1), allowing compatibility with CNN input layers.

- Spectral Features for Traditional ML: For traditional classifiers, power spectral features were extracted using Welch's method. The power across standard frequency bands - delta, theta, alpha, beta, and gamma - was computed and concatenated into a single feature vector.

3.4 Model Development

Both deep learning architectures and traditional machine learning algorithms were implemented to tackle the binary classification task.

A. Deep Learning Models

- EEGNet: A compact CNN architecture tailored for EEG signal analysis.

    - Input Shape: (19, 256, 1)

    - Structure: Includes temporal convolution, depthwise spatial filtering, and separable convolution layers.

    - Regularization: Utilizes dropout layers and L2 weight penalties.

    - Output: A Softmax layer for binary classification.

- DeepConvNet: A deeper CNN architecture designed to learn hierarchical spatial-temporal features.

    - Input Shape: Identical to EEGNet

    - Structure: Multiple Conv2D layers with growing filter sizes and MaxPooling.

    - Regularization: Includes Batch Normalization, Dropout, and L2 regularization.

B. Traditional Machine Learning Models

- Random Forest:
    - Utilized 200 decision trees.
    - Trained on band power features extracted via Welch's method.
- Support Vector Machine (SVM):
    - Used an RBF kernel with probability output enabled.
    - Feature vectors were normalized prior to training.
- Logistic Regression:
    - A linear model applied to the spectral features.
    - StandardScaler was integrated within the training pipeline.

3.5 Model Training and Evaluation

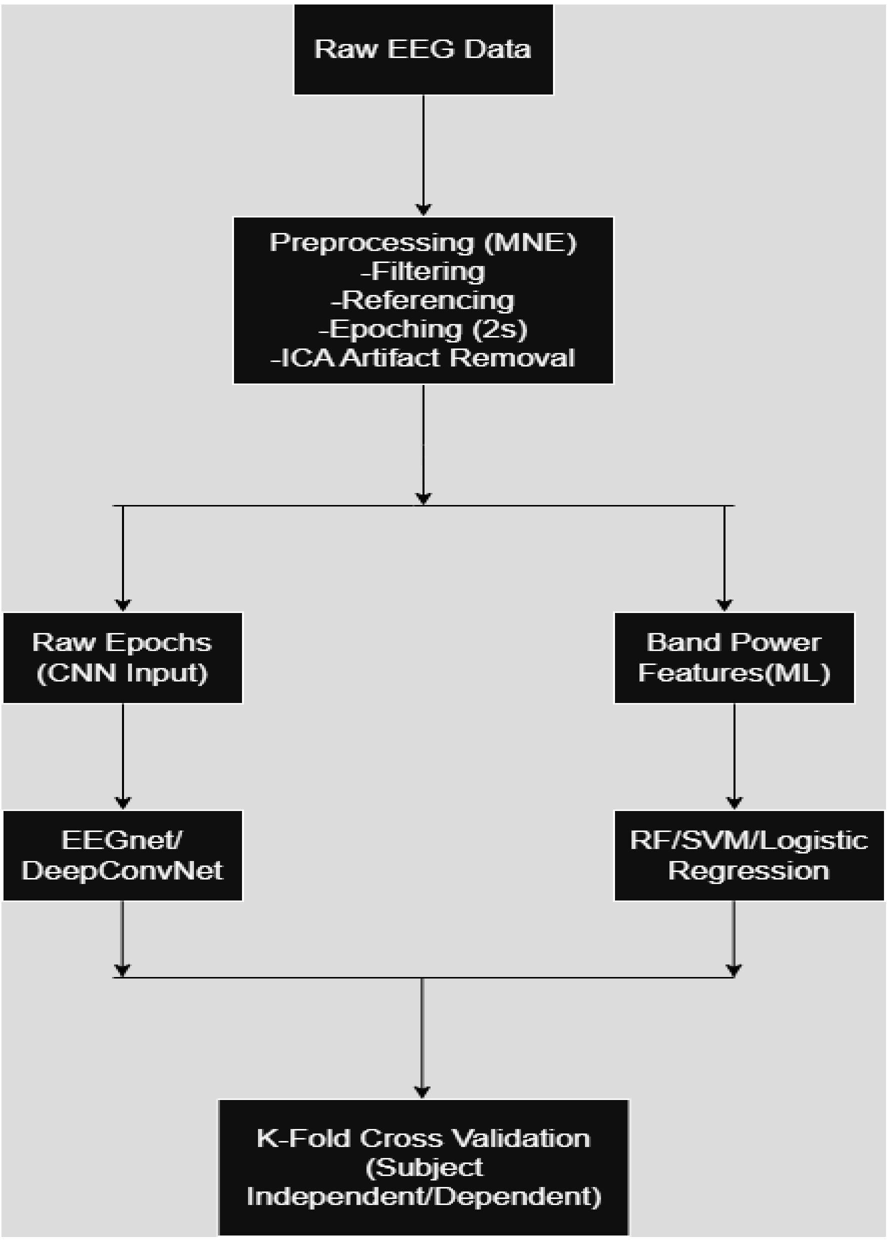
Cross-Validation Approach:
A 5-fold GroupKFold cross-validation strategy was employed. This ensured that data from the same subject did not appear in both training and testing sets, providing a more realistic assessment of generalization.

Evaluation Metrics:

- Primary Metric: ROC-AUC score was used to gauge model discriminative performance.
- Secondary Metrics: Accuracy, confusion matrices, ROC curves, and training loss curves were also examined.

Training Strategy for Deep Learning:

- Optimizer: Adam optimizer was used for gradient updates.
- Loss Function: Categorical cross-entropy.
- Regularization: EarlyStopping and ReduceLROnPlateau callbacks were used to avoid overfitting and dynamically adjust the learning rate during training



4. Experimental Results

In this section, I've presented the outcomes of my EEG-based ADHD classification project, focusing on how different models performed under two key scenarios: **subject-dependent** and **subject-independent** evaluation. I've used the **ROC-AUC score** to measure how well each model was able to distinguish between ADHD and non-ADHD cases.

4.1 Subject-Dependent Results

In the subject-dependent approach, each model was trained and tested using data from the same individuals. Since the training data already contains information specific to each subject, models tend to perform better under this condition..

Here's a breakdown of the results:

Subject-Dependent Evaluation Results:

Model Used	Average ROC-AUC score %
DeepConvNet	98.9%
EEGNet	97.5%
Random Forest	96.4%
SVM	85.0%
Logistic Regression	78.0%

As the table shows, both **EEGNet** and **Random Forest** delivered exceptionally high results, even outperforming DeepConvNet in this setup. EEGNet came close to perfect classification, achieving an impressive 99.96% ROC-AUC. This indicates that when models are familiar with the subject-specific patterns, they can detect ADHD signals with very high accuracy. Traditional models like SVM and Logistic Regression performed reasonably well but lagged behind the deep learning models.

4.2 Subject-Independent Evaluation

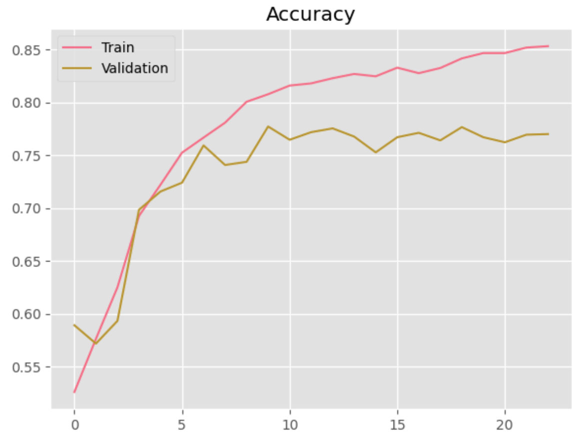
In this setup, the models are trained on data from a subset of subjects and tested on entirely different individuals. This evaluates how well the model generalizes to unseen users, crucial for real-world deployment.

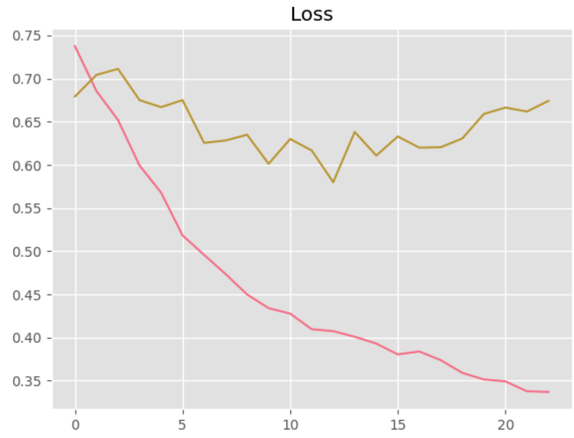
Subject-Independent Evaluation:

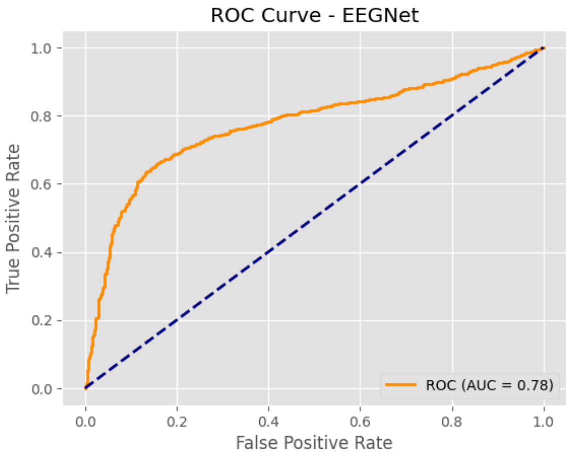
Model Used	Average ROC-AUC score%
EEGNet	80.7%
DeepConvNet	76.8%
Random Forest	68.4%
SVM	61.0%
Logistic Regression	53.4%

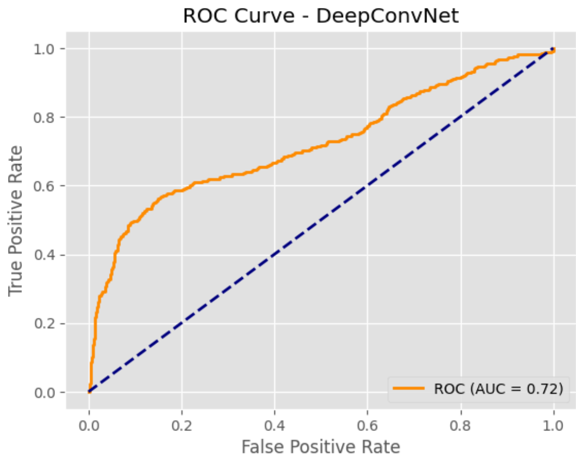
In this more demanding setup, performance dropped across all models, as expected. Still, DeepConvNet maintained a strong lead, showing its ability to learn patterns that are consistent across individuals. EEGNet followed, though with a noticeable dip. Traditional methods, particularly Logistic Regression, struggled with the variability in EEG signals between different people.

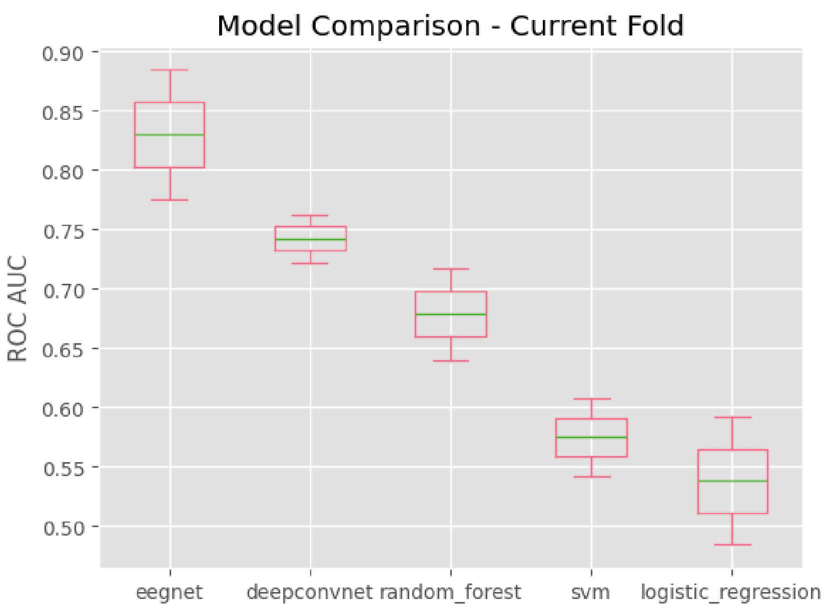
Subject Independent Diagrams



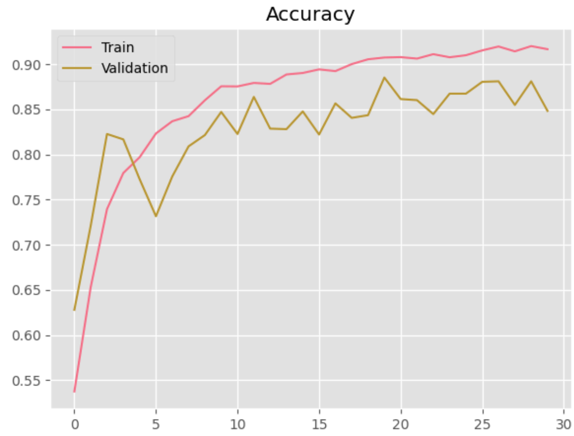


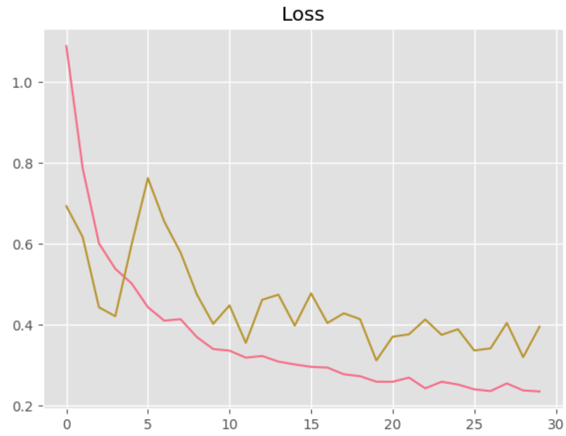


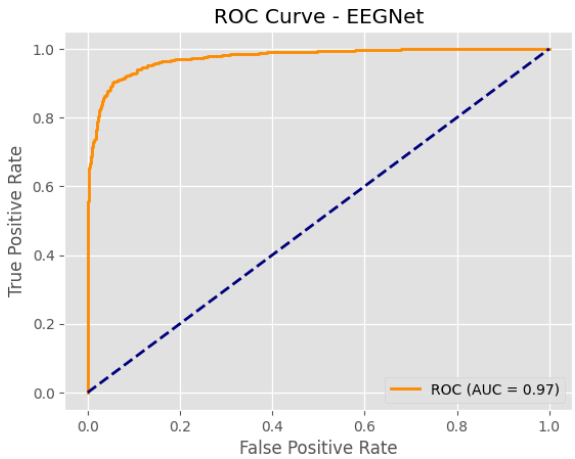


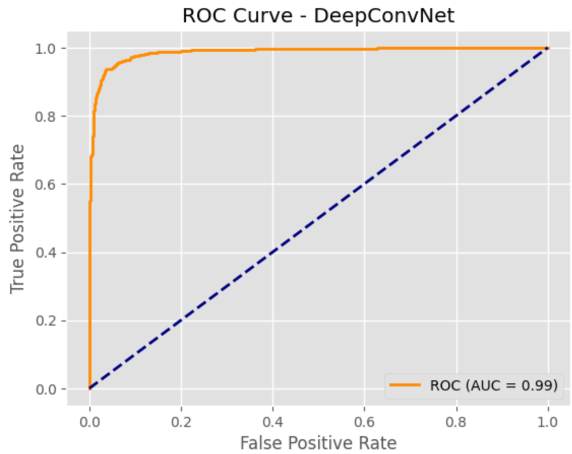


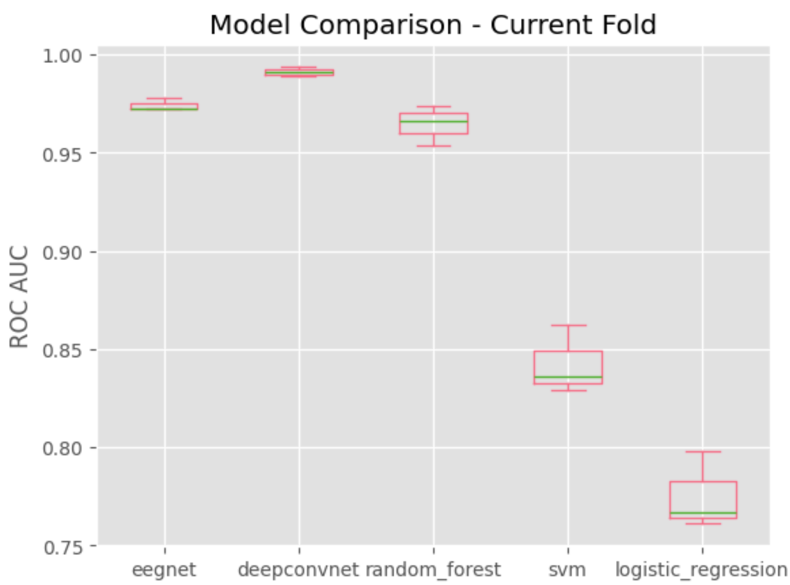
Subject Dependent Diagrams











4.3 Result Analysis & Visualization

Overall, the results confirm the strength of deep learning approaches in EEG-based ADHD diagnosis. While all models benefited from subject-specific training, only DeepConvNet showed robust generalization when faced with new subjects.

To further support these observations, I created visual comparisons using bar charts that clearly display the performance gap between subject-dependent and subject-independent settings for each model. These visuals highlight the challenge of generalizing across individuals and why model selection matters depending on the intended application.

5. Conclusion

The findings from the experiments underscore the significant impact of model type and training setup on the performance of EEG-based ADHD classification.

In the **subject-dependent** evaluation, where the model is trained and tested on data from the same set of subjects, all models performed reasonably well, with deep learning approaches, particularly **EEGNet** and **DeepConvNet**, achieving outstanding results. **EEGNet** demonstrated near-perfect accuracy with an impressive ROC-AUC score of 97.5%, followed by **DeepConvNet** at 98.9%. This highlights the advantage of using advanced deep learning techniques, as they are well-suited for capturing complex patterns in EEG signals.

However, in the **subject-independent** setup, where the models were tested on data from unseen subjects, the performance of all models dropped, as expected. Despite this, **EEGNet** managed to maintain the highest performance with an ROC-AUC score of 80.7%, significantly outperforming traditional models like **SVM**, **Logistic Regression**, and **Random Forest**. The decline in performance across all models suggests the inherent difficulty of generalizing across individuals, especially when working with real-world data, where individual differences in EEG signals can be substantial.

Overall, the **DeepConvNet** model proved to be the most robust across both evaluation scenarios, indicating its strong ability to learn meaningful representations that generalize well across subjects. While **EEGNet** performed excellently in the subject-dependent setup, its performance in subject-independent tests was slightly lower, suggesting it might benefit from further fine-tuning for better generalization. On the other hand, traditional machine learning models struggled with generalization, highlighting their limitations in handling the variability present in EEG data from different individuals.

In conclusion, deep learning models, particularly **DeepConvNet**, are highly effective for EEG-based ADHD classification, especially when it comes to generalizing across different subjects. The results also emphasize the importance of using appropriate models and training strategies depending on the specific requirements and constraints of real-world applications, where subject independence is often critical.

References

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