Detailed EEG Data Analysis Project Report

Introduction

This report presents the detailed results of an EEG data analysis project focused on classifying different cognitive states using advanced deep learning techniques. The dataset used is the Mental Arithmetic Tasks Dataset available at PhysioNet, which contains files for 36 subjects, each divided into two parts.

The objective of this study is to explore the effectiveness of two deep learning models, EEGNet and Vision Transformer (ViT), in accurately classifying cognitive states based on EEG data.

Methodology

The methodology section outlines the process from data collection to model evaluation.

Data Collection:
The dataset was sourced from PhysioNet's Mental Arithmetic Tasks Dataset. It comprises EEG recordings from 36 subjects performing various cognitive tasks. Each subject's data is divided into two parts, providing a comprehensive set of signals for analysis.

Data Preprocessing:
The EEG data was preprocessed using the Python MNE library. Preprocessing steps included:
- Noise Reduction: Techniques such as band-pass filtering were applied to remove noise and artifacts.
- Feature Extraction: Power Spectral Density (PSD) analysis was conducted to extract relevant

features from the EEG signals.

Model Descriptions:

EEGNet:

EEGNet is a compact convolutional neural network designed specifically for EEG-based brain-computer interfaces. It consists of multiple layers, including convolutional, pooling, and dropout layers, which help in capturing the spatial and temporal characteristics of EEG signals.

Vision Transformer (ViT):

The Vision Transformer (ViT) applies a transformer architecture to image patches, treating them as sequences. For this project, the EEG data was converted into image-like representations, enabling the ViT to process the data. The ViT model leverages self-attention mechanisms to capture complex dependencies in the data.

Model Training and Evaluation

Training Procedure:

Both models were trained using a supervised learning approach. The dataset was split into training and testing sets to evaluate model performance. Key hyperparameters such as learning rate, batch size, and number of epochs were fine-tuned for optimal results.

Evaluation Metrics:

The following metrics were used to evaluate model performance:

- Accuracy: The proportion of correctly classified instances out of the total instances.

- Precision: The proportion of true positive instances out of the total predicted positive instances.

- Recall: The proportion of true positive instances out of the total actual positive instances.

- F1 Score: The harmonic mean of precision and recall, providing a balanced measure of the model's performance.

Results

The performance of the models on the test set is summarized below:

EEGNet:

- Accuracy: 48.87%
- Precision: 43.53%
- Recall: 6.41%
- F1 Score: 11.18%

Vision Transformer (ViT):

- Accuracy: 48.78%
- Precision: 48.27%
- Recall: 28.94%
- F1 Score: 36.19%

The results indicate that both models performed similarly in terms of accuracy. However, the Vision Transformer (ViT) showed significantly better precision, recall, and F1 score compared to EEGNet. This suggests that while both models are effective, the Vision Transformer might be more suitable for this specific EEG classification task.

Conclusion

This detailed report presents a comprehensive analysis of EEG data using two deep learning models: EEGNet and Vision Transformer (ViT). The findings suggest that the Vision Transformer outperforms EEGNet in terms of precision, recall, and F1 score, making it a potentially more effective model for EEG classification tasks.

Further optimization and exploration of different model architectures could enhance the performance of these models. Future work could involve experimenting with additional preprocessing techniques, tuning hyperparameters, and exploring other deep learning architectures to improve classification accuracy.