EEG Motor Imagery Classification using Integrated Transformer-CNN for Assistive Technology Control

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***Abstract*—Neuromuscular disorders encompass pathological conditions affecting either the musculoskeletal system, the nervous system, or their interface. The majority of neuromuscular disorders lack complete curative treatments and thus necessitate efforts focused on improving rehabilitation and quality of life. Assistive technologies with brain-computer interface (BCI) control provide a promising solution to main patients' daily activities. Central to these technologies is the classification of electroencephalography (EEG) motor imagery signals, which is paramount for the operational success of BCIs. The endeavor to enhance the precision of these classifications has led to the exploration of various computational techniques, with convolutional neural networks (CNNs) being at the forefront due to their proficiency in handling spatial hierarchies in data. Despite the advancements, the quest for improved accuracy continues, especially in scenarios characterized by raw EEG data inputs, as opposed to the transformed data inputs (e.g., using Fast Fourier Transform (FFT)) commonly reported in existing literature. This study introduces an integrated CNN model augmented with a transformer encoder block, aiming to harness the inherent spatial-temporal features of EEG signals more effectively. Preliminary evaluations suggest an encouraging comparable performance with the studies reported in the field, thereby underscoring its potential utility in enhancing motor imagery classification for BCI applications.**

***Index Terms*—EEG, motor imagery classification, Convolutional Neural Networks (CNN), transformer encoder, BCI**

I. Introduction

Brain-computer interfaces (BCIs) [1] have emerged as a key component in the advancement of assistive devices and rehabilitation approaches [2], which have been inaugurated by the convergence of neural engineering and healthcare technology. Among the myriad of signals utilized for BCI, electroencephalography (EEG) based motor imagery classification presents a non-invasive gateway to understanding and interpreting the intentions of the human brain [3]. Recent investigations have predominantly leveraged CNNs to decode these signals, given their adeptness at capturing spatial features [4], [5]. However, the variability in optimal convolution scales across individuals and the challenge of limited training data remain hurdles to achieving high classification accuracy. Acknowledging these challenges, this study proposes an approach that synergizes the spatial feature extraction capabilities of CNNs with the encapsulation of the temporal dynamics facilitated by transformer encoder blocks. This combination aims to create a more holistic understanding of EEG data, mainly when dealing with raw signal inputs, thus steering clear of the pre-processing steps introduced by methods like FFT. The results highlight the proposed model's capability to achieve notable accuracy in motor imagery classification, suggesting a promising avenue for future research and application in BCI-driven healthcare solutions.

II. Network Architecture and Methodology

In this study, the BCI Competition IV 2a dataset [6] was used to evaluate the proposed method. This dataset includes EEG recordings from 9 subjects across four motor imagery tasks, i.e., the imagination of movement of the left hand, right hand, both feet, and tongue. This dataset, comprising two sessions per subject with 288 trials each, was recorded using twenty-two Ag/AgCl electrodes with a sampling frequency of 250 Hz. In the preprocessing, a bandpass filter from 0.5 to 40 Hz was applied to the data to focus on the frequency ranges most relevant to motor imagery tasks.

In this study, we proposed an integrated CNN model enhanced by a transformer encoder block, designed to better utilize the intrinsic spatial-temporal characteristics of EEG signals as shown in Fig. 1. Initially, the convolutional layers conduct spatial feature extraction, and subsequent to this phase, the transformer encoder discerns temporal patterns. This layered approach ensures thorough processing, which is pivotal for the intricate patterns characteristic of EEG data. The model's strategic design is geared towards enhancing feature representation prior to the classification stage, where the interpreted features are utilized for predictive analysis.

The model is trained to differentiate between left and right-hand movement imagery tasks without transforming the data into the frequency domain. The proposed network combines CNNs with transformer encoder blocks to classify EEG signals. This approach leverages the spatial and temporal dynamics of EEG data for robust feature extraction, while directly using raw signals to avoid preprocessing steps. The network architecture begins with convolutional layers to extract spatial features from the EEG signals, followed by a transformer encoder that captures the temporal dynamics, emphasizing the direct use of raw EEG signals.

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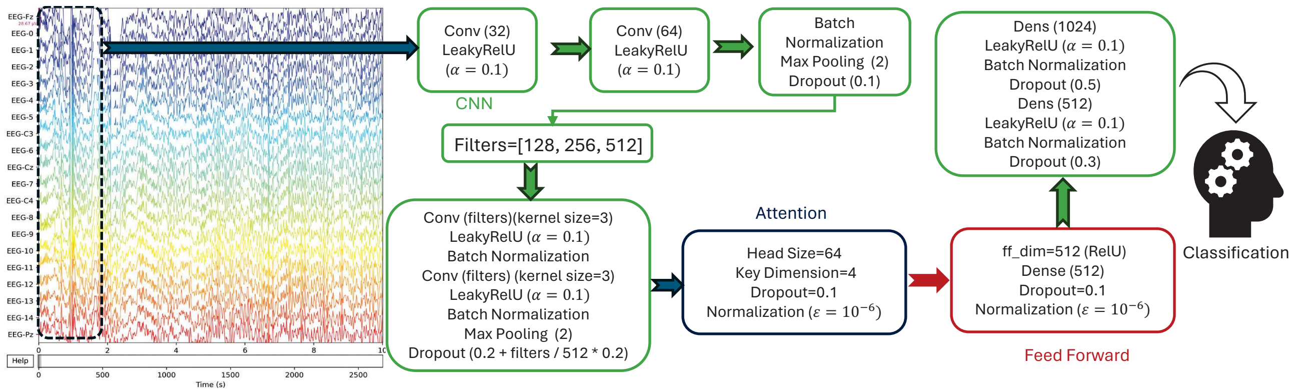

Fig. 1. Hybrid CNN-transformer network architecture for motor imagery classification.

III. Results and Conclusion

The model's performance, delineated in Table I, provides a quantitative insight into its efficacy across various subjects. The mean accuracy across subjects is 0.753, indicating a relatively consistent performance with a moderate variance, reflecting the robustness of the model in dealing with different EEG patterns. The F1 Score, averaging at 0.837, suggests a high degree of precision and recall, a crucial factor for reliable BCI applications. Lastly, the Cohen's Kappa score of 0.670 further corroborates the model's validity, signifying a substantial agreement beyond chance between the predicted and observed classifications. These metrics collectively affirm the model's potential as a reliable tool for EEG motor imagery classification, setting a groundwork for subsequent advancements in non-invasive BCI healthcare technologies.

The results underscore a notable variation in the model's performance across different subjects. While the model achieved commendable validation accuracy and F1 scores for certain participants, there is evidence of lower performance metrics for others. This disparity suggests that while the model can capture and classify EEG motor imagery signals effectively for some subjects, it may not generalize equally well across all individuals. The variance, as evidenced by the range in Cohen's Kappa scores, indicates that the algorithm does not perform uniformly across the dataset.

The need for a tailored approach for each subject is clear, and this could potentially be addressed by incorporating adaptive learning techniques such as reinforcement learning. By employing a reinforcement learning framework, the model could dynamically adjust to the unique EEG signal patterns of each individual, thereby potentially enhancing the classification accuracy for those subjects where the current model does not perform as well. This individualized learning strategy might prove pivotal in advancing the reliability and efficacy of BCI technologies.

TABLE I
Comparative Analysis of Model Performance Metrics across Subjects, Showcasing Accuracy, F1 Score, and Cohen's Kappa.

ID	Accuracy (%)	F1 Score	Cohen's Kappa
1	74.6	0.815	0.654
2	63.6	0.733	0.470
3	76.9	0.857	0.724
4	72.9	0.786	0.603
5	88.8	0.963	0.931
6	81.1	0.938	0.861
7	71.8	0.786	0.586
8	70.1	0.759	0.522
9	77.6	0.900	0.678
Mean ± Std	75.3 ± 7.1	0.837 ± 0.081	0.670 ± 0.151

IV. Acknowledgments

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