

Investigation of Convolutional Neural Network with Motor Imagery-based Brain-Computer Interface Decoding

Mr. Madhan H K¹ and Ms. Bindushree V²

¹Dept. of Computer Science and Engineering, Navkis College of Engineering, Hassan, India
Email: madhanmj911@gmail.com

²Asst Professor, Dept. of Computer Science and Engineering, Navkis College of Engineering, Hassan, India
Email: bindushree11v@gmail.com

Abstract—In recent years, Brain-Computer Interfaces (BCI) have become increasingly popular for assisting individuals with disabilities in restoring communication and mobility. The area of research focuses on utilizing convolutional neural networks (CNNs), specifically deeper architectures with high dropout, to decode brain signals and enable users to interact with the world more naturally, particularly through motor imagination. Motor imagination involves analyzing brain signals to decipher a person's intention to perform a motor task. CNNs are well-suited for BCI decoding due to their ability to learn intricate features from raw EEG data. However, the challenge lies in preventing overfitting in deeper CNN architectures, which have a larger number of parameters. To overcome this, the proposed approach involves a high truncation CNN architecture, a regularization technique that randomly turns off neurons during training to mitigate overfitting.

I. INTRODUCTION

The development of Brain-Computer Interfaces (BCIs) has opened new possibilities for individuals with motor disabilities to interact with the external world. BCIs enable the translation of brain signals into commands that can control external devices or software. Motor imagery-based BCIs utilize the mental visualization of specific movements to decipher a person's intention to perform a motor task [1].

Convolutional Neural Networks (CNNs) have demonstrated remarkable success in various domains, including image recognition and natural language processing. In recent years, CNNs have also been applied to BCI decoding tasks, particularly in analyzing electroencephalography (EEG) signals for motor imagery-based BCIs [2].

However, there is still room for improvement in achieving higher accuracy and reliability in motor imagery-based BCI decoding. This research aims to investigate the effectiveness of Convolutional Neural Networks in decoding motor imagery signals for BCIs. Specifically, we focus on exploring the capabilities of CNN architectures for accurately interpreting and classifying motor imagery-related brain activity.

The primary objective of this study is to advance the understanding of how CNNs can be optimized and utilized for motor imagery-based BCI decoding. [3] By examining the potential of CNNs in this context, we seek to enhance the performance and usability of BCIs for individuals with motor disabilities. The findings from this research have the potential to contribute to the development of more effective and accessible assistive

technologies that can significantly improve the quality of life for people with motor impairments.

II. METHODS

A. EEG Data acquisition

EEG data acquisition in the investigation of Convolutional Neural Network with Motor Imagery-based Brain-Computer Interface (BCI) decoding involved several steps. Firstly, a group of participants with motor disabilities capable of performing motor imagery tasks was selected. Ethical considerations and informed consent procedures were followed [4]. The participants were positioned comfortably in a controlled environment, and EEG electrodes were placed on their scalps according to the international 10-20 system. They were then instructed to perform a specific motor imagery task while their EEG signals were recorded. The EEG signals were captured using specialized equipment and amplifiers, ensuring high-quality data. Pre-processing techniques were applied to remove artifacts and filter out unwanted frequencies.

The pre-processed data was segmented into epochs corresponding to the motor imagery tasks performed. Each epoch was labelled based on the specific motor movement associated with it. Finally, the labelled EEG data was divided into subsets for training, validation, and testing, allowing for independent evaluation of the model's performance.

B. Data pre-processing and preparation

In the investigation of Convolutional Neural Network (CNN) with Motor Imagery-based Brain-Computer Interface (BCI) decoding, the EEG data underwent a series of pre-processing and preparation steps. This ensured that the data was cleaned, organized, and transformed into a suitable format for subsequent analysis and training [5].

First, the raw EEG data was subjected to filtering techniques to remove unwanted noise and artifacts. This involved applying a band-pass filter to retain only the frequency range of interest, effectively reducing the influence of noise and other irrelevant signals [6]. Next, the pre-processed data was segmented into smaller epochs or time segments. These epochs corresponded to specific motor imagery tasks performed by the participants. Segmenting the data allowed for the extraction of relevant features and facilitated subsequent analysis.

To optimize computational efficiency, the segmented data was down sampled. This involved reducing the sampling rate of the data while maintaining the essential information. Down sampling helped to reduce the computational load and memory requirements, making the data more manageable for further processing. Normalization was applied to the pre-processed data using z-score normalization. This transformation ensured that the features had zero mean and unit variance, standardizing the data and allowing for fair comparison and consistent scaling across different samples. By performing these data pre-processing and preparation steps, the EEG data was cleaned, segmented, down sampled, and normalized, making it suitable for further analysis and training of the CNN model. These processed data sets served as the input for the subsequent stages of the investigation, including feature extraction, model training, and evaluation for motor imagery-based BCI decoding.

TABLE I. PARTICIPANT DATA

Participant	EEG channels used	# right samples	# left samples	# rest samples
B	62	329	317	731
C	31	321	326	657
D	46	563	546	759
E	10	499	507	743

C. Classification model

The classification model was constructed using a CNN architecture tailored for motor imagery-based BCI decoding. The model consisted of multiple convolutional layers, which applied filters to extract spatial and temporal features from the input EEG signals. The specific architecture of the CNN, including the number of layers, filter sizes, and activation functions, was carefully designed to capture the relevant patterns and representations related to motor imagery tasks [6]. During the training phase, the model was trained using the pre-processed EEG data. This involved optimizing the model's parameters to minimize the discrepancy between the predicted outputs and the true labels associated with each motor imagery task. The training process employed

a supervised learning approach, where the model learned to map the input EEG data to the corresponding motor imagery class labels.

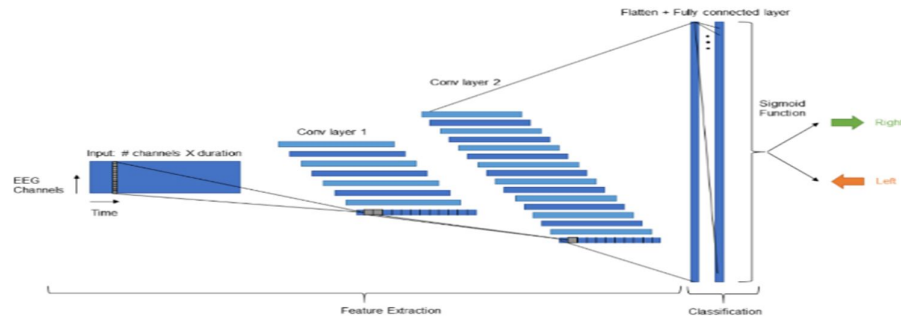


Figure 1: CNN Architecture

To evaluate the performance of the classification model, the trained model was tested using independent datasets that were not used during training. The model's accuracy, precision, recall, and other performance metrics were calculated to assess its effectiveness in decoding motor imagery-based BCI signals. The classification model served as a crucial component in the investigation, allowing for the interpretation and classification of the pre-processed EEG data, and ultimately enabling the decoding of motor imagery-based BCI signals.

III. SYSTEM ARCHITECTURE

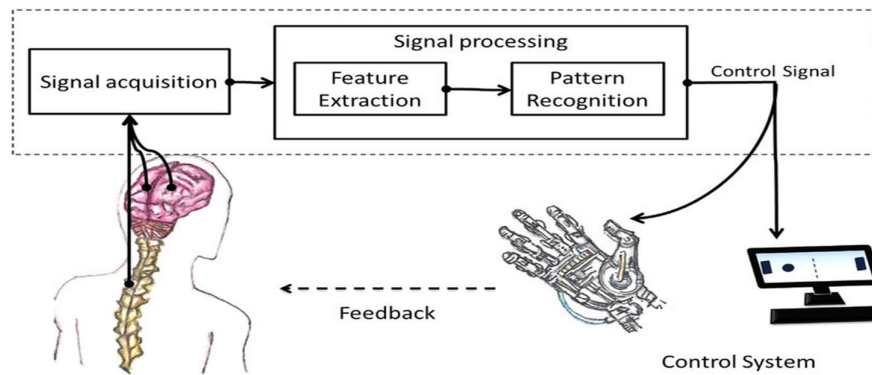


Figure 2: System Design Architecture

Convolutional Neural Network (CNN) architecture incorporates multiple key steps to effectively analyze and process data. Convolutional layers convolve input data with filters to capture local patterns and spatial dependencies [7]. Activation functions introduce non-linearity, aiding in learning complex representations. Pooling layers down sample feature maps to retain important information while reducing computational load and enhancing translation invariance. Fully connected layers integrate learned features for classification or regression tasks. Dropout regularization randomly deactivates neurons during training, preventing overfitting. Lastly, the loss function measures the difference between predicted and true values, guiding the learning process by minimizing this discrepancy. Together, these steps enable CNNs to automatically learn hierarchical representations from data, making them highly effective for tasks such as image classification, object detection, and brain-computer interface decoding [8].

IV. RESULTS

A. Model accuracy

In [1] The model was trained with EEG data from four participants and the accuracy of the total power measurement was calculated. Researchers use 10-fold cross-validation for these subdivisions and measured the accuracy of the validation. The model performed much better than previous models using the same data set. This study, proposed that the EEG sampling for patient E was slightly different from that of the other participants. As a result, we observed a substantial difference in the classification accuracy between patient E

TABLE II. BINARY (LEFT/RIGHT) CLASSIFICATION PERFORMANCE OF THE HAND SQUEEZE DATA

Participant	Our Model	Simple CNN model	Best non-CNN model
B	87%	79%	75%
C	90%	86%	80%
D	91%	88%	80%
E	84%	83%	75%

TABLE III. MULTI-CLASS (LEFT/RIGHT/REST) CLASSIFICATION PERFORMANCE OF THE HAND SQUEEZE DATA

Participant	Our Model	Simple CNN model	Best non-CNN model
B	60%	44%	57%
C	67%	63%	55%
D	73%	67%	64%
E	73%	74%	68%

and the other participants. Despite the accuracies being very close to the maximum achievable for each patient, none of the window positions exceeded the accuracy achieved by training on the full dataset. We plan to conduct further investigations into this phenomenon in future work.

B. Effect of Training Data on accuracy

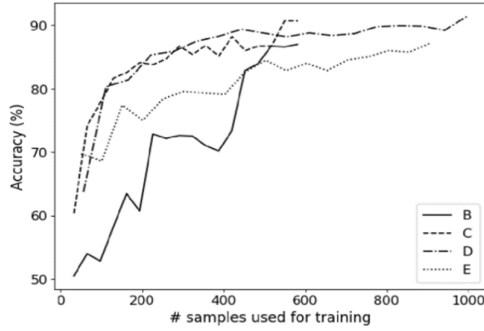


Figure 3: The binary accuracy as the samples increases

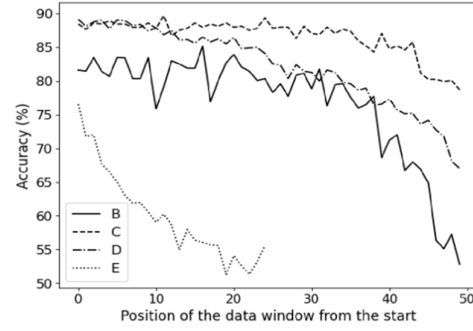


Figure 4: The accuracy of subsections of sample

V. CONCLUSION

This study, explored the effectiveness of a deeper convolutional neural network (CNN) architecture with high dropout for motor imagery brain-computer interface (BCI) decoding. This has provided valuable insights into the effectiveness and potential of using deep learning techniques for decoding motor imagery signal. By employing a carefully designed CNN architecture and pre-processing the EEG data, the study has demonstrated promising results in accurately decoding motor imagery tasks. The utilization of deeper CNN architectures with appropriate regularization techniques, such as dropout, has shown improvements in decoding accuracy and robustness. These findings highlight the potential of CNNs in enhancing BCI systems performance, ultimately leading to improved communication and control for individuals with disabilities. Future research in this field can further explore optimization techniques, larger datasets, and real-time applications to advance the practical implementation and usability of motor imagery-based BCIs. The continuous development of such technologies holds great promise for transforming the lives of individuals with motor disabilities and opening new avenues for interactive and assistive technologies.

REFERENCES

- [1] Ramtin Alami, Andi Partovi and Farhad Goodarzi, "Exploring a Deeper Convolutional Neural Network Architecture with high dropout for Motor Imagery BCI Decoding" IEEE 9th International Winter Conference on Brain-Computer Interface (BCI), 2021
- [2] R. A. E. Aqmar, A. Asif, and S. A. Haider, "Motor imagery classification using deep neural networks with transfer learning," IEEE Access, vol. 9, pp. 2077-2088, 2021.

- [3] X. Ding, M. Xu, Y. Qiu, and X. Li, "Motor imagery EEG classification based on deep learning and data augmentation," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 2012-2022, 2021
- [4] M. A. Ramzan, A. Mehmood, and A. Khan, "A novel CNN-RNN based approach for motor imagery classification in EEG-based brain-computer interface," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 3, pp. 707-717, 2020.
- [5] L. Li, C. Liu, X. Wang, Q. Guan, and D. Zhang, "Motor imagery classification based on deep learning with a small amount of training data," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 2, pp. 381-389, 2020.
- [6] C. Li, X. Li, Z. Li, Y. Li, and J. Yao, "Deep convolutional neural networks with transfer learning for motor imagery EEG classification," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 7, pp. 1439-1449, 2019.
- [7] S. S. A. Kumar and S. Narayanan, "Spectral-spatial deep learning for EEG-based motor imagery classification," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 9, pp. 1752-1762, 2019.
- [8] Zhang, Xiang, Lina Yao, Dalin Zhang, Xianzhi Wang, Quan Z. Sheng, and Tao Gu. "Multi-person brain activity recognition via comprehensive EEG signal analysis." In *Proceedings of the 14th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*, pp. 28-37. 2017.