Enhancing Motor Imagery based Brain Computer Interfaces for Stroke Rehabilitation

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ABSTRACT

Globally, the prevalence of disabilities among stroke survivors exceeds 80%, with upper-limb movement impairments affecting over 85% of individuals. To address this challenge, motor imagery (MI) based brain-computer interface (BCI) has emerged as a promising approach for translating the imagined motor intentions of individuals into control signals for external devices. Electroencephalography (EEG) signals are commonly used in MI-BCIs due to their non-invasiveness, portability, high temporal resolution, and affordability. The present study utilized the publicly available Electroencephalography Motor Movement/Imagery Dataset (EEGMMIDB), comprising 64-channel EEG recordings from 109 participants sampled at 160 Hz. The aim was to classify between the opening/closing of palms and feet using the Long Short Term Memory (LSTM) network directly on cleaned EEG signals, bypassing traditional feature-extraction methods that are computationally intensive and time-consuming. We achieved an average classification accuracy of 71.2% across subjects by tuning the hyperparameters related to epochs and segment length. This research emphasizes the efficacy of deep learning approaches in generating robust control signals for predicting motor intentions using EEG signals, eliminating the necessity of laborious feature extraction methods. By leveraging deep learning models, MI-BCI devices can advance neuro-rehabilitation, especially in stroke, by providing motor assistance, enabling patients to execute movements solely through the power of imagination.

KEYWORDS

motor imagery, electroencephalography, LSTM, brain-computer interface, stroke, deep learning

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1 INTRODUCTION

Stroke, with an annual mortality rate of approximately 5.5 million and accounting for 116.4 million DALYs (disability-adjusted life-years), is a prominent global health concern and ranks as the second leading cause of death worldwide [11, 13]. Stroke patients who have survived stroke often exhibit upper limb hemiparesis, i.e., partial or complete paralysis of the upper limb on one side of the body [23]. Previous studies have demonstrated that a significant proportion of about 55-75% of stroke patients with hemiplegic arm experience persistent impairment in arm movement activities even after three to six months of rehabilitation [18]. These findings emphasize the necessity for the development of enhanced rehabilitation strategies to address the specific needs of stroke patients.

The current approach to stroke rehabilitation involves administering conventional therapy practices, including repetitive physical motor assistance or occupational therapy to stroke patients [12]. However, these methods overlook the crucial factors of patient engagement and motivation, which are essential for effective motor recovery [6]. Therefore, there is a need for advanced therapeutic approaches that can expedite the recovery process while simultaneously providing motor assistance to patients. Motor Imagery (MI) enables individuals with hemiplegia, paraplegia, and tetraplegia to utilize their ability to imagine motor movements [10]. MI promotes neuroplasticity [21] by activating the same brain regions as in actual motor execution and planning, thus stimulating neuroplasticity [39] in the motor cortex. BCIs are artificial devices that employ an unconventional approach to establish direct communication between neuronal electrical signals and external devices circumventing the traditional pathway from the central nervous system to the muscular system for motor movement [33]. MI-BCI systems not only harness the power of neuroplasticity but also introduce a dynamic, interactive, and adaptable system that can be personalized for each patient. These systems offer a means to restore motor function for stroke patients by providing a direct pathway to translate their motor imaginations into control signals for external devices, such as prosthetic limbs and robotic arms. Various non-invasive methods are used to record brain activity, such as EEG (Electroencephalography), fNIRS (functional near-infrared spectroscopy), etc. We prefer using EEG as they offer a high temporal resolution, are non-invasive, and are cost-effective [19, 30]. EEG-BCI systems are used to classify MI signals, which are rhythmic oscillations of motor movement captured over the sensorimotor cortex within the mu and beta frequency bands [42]. MI-EEG-BCIs provide real-time feedback to users about their brain activity, enabling self-modulation for improved motor function, control, and coordination [28].

Study	Movement Type	Features	Classifier	Accuracy
Athif et al. [3]	Left/Right Hands/Feet	WaveCSP	LDA SVM KNN	63.4% 63.4% 63.5%
Paul et al. [31]	Left/Right 10 movements	FBCSP	SVM	91.5%
Yi et al. [43]	Compound Limb	Multi-sTRCSP	SVM	70.0%

Table 1: Comparison with relevant research in MI-BCI

Decoding movement-related brain activity and underlying brain representations in response to environmental stimuli and user desires is a challenging task. Studies focused on developing MI-BCI systems have predominantly been conducted on healthy participants [20, 41]. However, the methodologies employed and the results obtained are highly adaptable and applicable to a broader audience, underscoring their relevance and transferability. Early research has focused on classifying left vs. right hand/foot or direction of hand movement [5]. Recent research has focused on deploying various Machine Learning and Deep Learning techniques to improve accuracy score [2]. Advancements in deep learning techniques, such as using Convolutional Neural Networks (CNNs), have shown considerable results by precisely decoding and visualizing the spatial dynamics of EEG signals [9, 36]. Hongli et al. [26] have explored using a combined architecture of CNN and Recurrent Neural Network (RNN) to capture both temporal and spatial characteristics of EEG data effectively. Although promising, the combination has certain limitations; for example, the paper did not assess their model with Independent Identically Distributed (i.i.d.) samples. The model considered many parameters making it computationally heavy. Researchers have also used feature engineering and machine learning approaches to classify brain states. They have used features such as power spectral density [8] and spectral coherence [34] as inputs to classical machine learning classifiers for the task. The accuracy of MI-BCI systems is affected by challenges such as low signal-to-noise ratio (SNR), and neuroplasticity [37]. Additionally, MI-EEG signals represent complex patterns in the brain signals, which may not be easily captured by linear classifiers. Individual differences, such as the ability to precisely imagine motor movements or MI aptitude, also affect Brain Machine Interface (BMI) control. High aptitude BMI users reflected higher MI accuracies analyzed using behavioral differences in kinaesthetic and visual MI [29]. Limited literature exists on the classification of motor imagery involving both hands and feet, while there has been extensive research on classifying the left/right hand and foot movements. A combination of Wavelet Common Spatial Patterns (WaveCSP) for feature extraction and Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and k-Nearest Neighbors (KNN) for classification of left/right hand has achieved an average accuracy of 63.40%, 63.40%, and 63.50%, respectively [3]. Another study achieved an accuracy of 91.50% for classifying left/right hand with ten movements using Filter Bank Common Spatial Patterns (FBCSP) for feature extraction and SVM as a classifier [31]. However, despite the high accuracy, the model's compatibility and generalizability are considerably low for training and testing on large datasets. MI-BCI devices, thus, regularly require intensive updation of algorithms to comprehend motor intentions and reliably control external devices like prosthetic limbs. Previous studies [27] have demonstrated the efficacy of LSTM models in analyzing dynamic temporal and subject-dependent data, such as EEG signals. Our LSTM model, with its ability to model non-linear relationships, captures intricate temporal dynamics and has a higher capacity to learn and represent these complex patterns.LSTM model owing to its excellent generalization abilities [40], has been used in this study to ensure robust generalization across our extensive dataset of 109 participants and significantly capture broad patterns. While traditional feature extraction techniques have been widely used, they may not always be the optimal choice. These methods often rely on manual design and domain knowledge to define relevant features, which can be time-consuming, labor-intensive, and task-specific. However, our LSTM model offers an inherent property of extensive feature engineering steps, which facilitates time-effectiveness [42].

In this study, we also explored various combinations of feature extraction and classification techniques for binary classification. We employed three distinct methods for the classification task, namely Common Spatial Patterns (CSP) with LDA, CSP with Random Forest, and CSP with SVM.

2 METHODOLOGY

In this section, we take an in-depth look at the dataset, feature extraction and classification algorithms, and the experiment analysed in the study.

2.1 Dataset Information

In this study, we used the Electroencephalography Motor Movement/Imagery Dataset (EEGMMIDB), a publicly available dataset hosted on PhysioNet [14]. A BCI2000 system [35] was used to collect and synchronize the 64-channel EEG recordings using the internationally recognized 10-20 system for electrode placement. The data was collected for 109 participants at a sampling frequency of 160 Hz when they performed four different tasks, which are mentioned below:

1. **Task 1**: Target appears on the left or right side of the screen-Subject opens and closes the corresponding hand. The subject relaxes.
2. **Task 2**: The subject *imagines* performing task 1.
3. **Task 3**: If the target appears on the top, the subject opens and closes both hands; if the target appears at the bottom, the subject opens and closes both feet. The subject relaxes.
4. **Task 4**: The subject *imagines* performing task 3 as depicted in figure 1.

Two baseline runs lasting for about one minute each with eyes open and closed were performed at the beginning of the experiment. Subsequently, three experimental runs of two minutes each, of the four tasks were performed in a task sequential order as listed above. Each subject performed 14 such trials, and each task lasted for at least 4 seconds. The order can be summarised as given in figure 1 below.

This dataset was particularly chosen as it records data from a large number of participants (109). Typically, stroke rehabilitation experiments include an average of 15 participants (including healthy and stroke-affected individuals). Badia et al. [20] have studied the promotion of cortical neuroplasticity using VR-based-MI-BCIs on nine healthy participants. Another study by Achanccaray

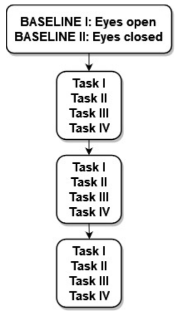

Figure 1: Description of each experimental task

[1] has explored improving the MI-BCI approach for stroke using different types of neurofeedback on twenty healthy individuals. A study by Škola et al. [38] has used embodied VR to enhance the efficacy of MI-BCIs on 30 healthy volunteers.

2.2 Machine Learning Approach

We used CSP to extract features and fed these features to machine learning classifiers such as Random Forest (LDA) and SVM from sklearn python library [32]. CSP is widely used for feature extraction in the MI-EEG domain. It spatially discriminates common features from the recorded brain activity to maximize variance for one class (task-related activity) while minimizing variance for another class (unrelated activity, noise). The classifiers used are mentioned below:

2.2.1 LDA. LDA is a supervised learning dimensionality reduction technique that maximizes the variance between two classes through a linear transformation. It classifies the data using a decision rule like a threshold value based on discriminant functions [4].

2.2.2 Random Forest Classifier. Random Forest classifiers are famous learning ensemble machine learning methods that randomly select features and training subsets from the data to give a final prediction. The ultimate prediction is based on the majority of votes gained by a particular class collectively from all decision trees [7].

2.2.3 SVM. SVM is a supervised-learning-based discriminative classifier that deals with high-dimensional feature space data. It fits the best hyperplane to classify data into binary or multiple classes [17].

2.3 LSTM Approach

In this study, we explored various feature extraction and classification methods, presented in Table 2, with a particular focus on the RNN-based Long Short Term Memory (LSTM) classifier [44].

The data was preprocessed and split into training and test sets. To facilitate convergence, featured data underwent reshaping and standard scaling. The neural network architecture used in the study comprised two main layers - an LSTM layer and a linear layer. The LSTM layer was made up of two LSTM cells, which accepted fixed-dimension input sequences representing features. A dropout operation was applied to the output sequence of the LSTM layer to mitigate overfitting. The output of the LSTM layer at the last time step was then processed by the linear layer to map it to a pre-determined number of output classes for binary motor imagery classification. The model was trained using the training data, optimizing the parameters through an Adam optimizer with a learning rate of 0.005 and utilizing the cross-entropy loss function. The evaluation was conducted on the testing data, with performance metrics such as accuracy, precision, recall, and F1-score computed. The area under the receiver operating characteristic curve (AUC) was also calculated to assess discriminative power. Predictions were compared to true labels, and a comprehensive analysis of the model's performance was performed, including the best test accuracy and AUC scores achieved for each subject. True labels and predicted labels were aggregated for all subjects to analyze the overall performance.

LSTM-based MI-BCIs offer dynamic and adaptive solutions to address the challenges posed by diverse stroke severities, patient demographics, and other individual differences [22]. The architecture of LSTMs captures retaining long-term dependencies and intricate EEG signal features across varied patient profiles, accounting for differences like age, gender etc. Their sequential processing captures patterns across a spectrum of stroke severities. Additionally, when trained with robust datasets, LSTMs can adapt to individual factors such as cognitive abilities or prior BCI exposure, ensuring tailored and efficient stroke rehabilitation.

Additionally, by considering variable-length sequences, the model accommodated the inherent variability in the durations of movement imaginations exhibited by individuals. It also efficiently extracted time-series features and retained spatial information through essential multi-channel temporal feature correlations from the hidden layer. Our model, thus, offers the advantage of end-to-end learning by learning directly from the raw EEG signals and outputs the predicted motor intentions. This eliminates the need for intermediate feature extraction steps and potentially improves the overall efficiency of the system.

2.4 Experiment

In the current study, we analyzed the EEG data for task 4, where the user *imagined opening or closing both hands/feet* on cue as displayed in figure 2. We implemented binary classification to distinguish between the two states, i.e., the intention of opening or closing of both hands vs feet. We used different combinations of feature extraction and classification methods as listed in table 2. While using LSTM, we varied hyperparameters such as the number of epochs and segment length to obtain the best set of parameters as given in table 3.

3 RESULTS

In this section, we present the results of the analysis conducted in this study. We used a combination of feature extraction and classification algorithms for the machine learning approach. Furthermore, we performed hyperparameter tuning to create a robust LSTM model to predict the EEG signals for hand movement vs. feet movement imagination across participants.

We began our analysis by using a combination of CSP and machine learning algorithms for feature extraction and classification, respectively. The initial combination investigated was the widely used CSP+LDA method for motor imagery classification, resulting in an accuracy of 59.3%. Subsequently, we employed the

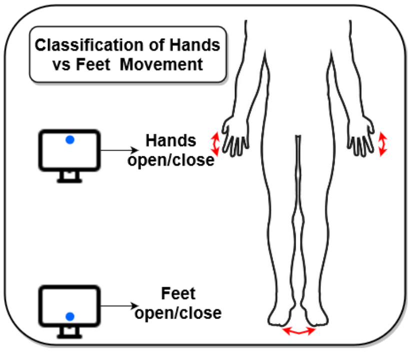

Figure 2: Task 4 containing a classification of hands vs. feet movement

CSP+Random Forest approach, which yielded an average test accuracy of 55.1%. To further improve motor imagery signal classification, the CSP+SVM method was employed and achieved a favorable accuracy score of 66.7%. Notably, both classes were balanced, with a chance level of 50%. Among these combinations, the CSP+SVM approach demonstrated the highest accuracy of 66.7%. A summary of these results is provided in table 2.

Feature Extraction	Classifier	Mean Test Accuracy
CSP	LDA	59.3%
	Random Forest	55.1%
	SVM	**66.7%**

Table 2: This table shows the classification of motor imagery signals using different feature extraction and classification methods. The sampling frequency is 160 Hz.

Next, we employed LSTM for end-to-end feature extraction and classification and explored various combinations of segment lengths and epochs. The maximum mean accuracy of 71.2% was achieved with 165 epochs, a segment length of 80 (equivalent to 0.5 seconds of data), and a learning rate of 0.005. The results obtained on hyperparameter-tuning are shown in the table 3.

4 DISCUSSION

Stroke rehabilitation has seen the evolution of multiple modalities aiming to improve the quality of life of patients in their Activities of Daily Living (ADLs) [15]. Traditional approaches such as Physiotherapy [25] and Constraint-Induced Movement Therapy (CIMT) [24] have been foundational in post-stroke recovery. Innovative techniques such as Mirror therapy and MI-based BCIs [16] have also been developed to induce neuroplasticity. However, a common limitation among the traditional modalities is the monotony and lack of consistent patient engagement, leading to decreased motivation and often leading the patient to quit the intervention before completion. In contrast, recent advancements have explored MI-based BCIs that have emerged as a promising approach in neurorehabilitation, particularly for individuals with motor impairments, such as stroke survivors. The patient-centric individualization, combined with real-time feedback mechanisms, ensures sustained patient engagement and motivation, making MI-BCIs a superior and more efficacious approach in stroke rehabilitation.

Epochs	Segment Length	Mean Test Accuracy
25	0.5s	66.7%
	1s	64.5%
165	**0.5s**	**71.2%**
	1s	67.1%

Table 3: This table depicts the results of MI classification using LSTM and hyper-parameter tuning. The sampling frequency is 160 Hz.

In this study, we predicted whether the participants imagined moving their hands or feet using EEG signals.

We performed binary classification using CSP+LDA, CSP+Random Forest, and CSP+SVM. We finally used LSTM to classify signals between the two mental states imagined in task 4 of EEGMMIDB.

In this paper, we achieved an average test accuracy of 71.2% (chance=50%) by fine-tuning the LSTM model for the within-subject binary classification. We observed that the LSTM model efficiently captures the temporal dynamics of electrical signals from 64 EEG channels. This method has shown promising results for supervised binary-class classification. Our study introduces the novel application of LSTM networks for motor imagery classification on a large EEGMMIDB dataset consisting of 109 participants. The model provides a more efficient approach that eliminates the need for computationally intensive feature extraction and allows flexibility in handling variable-length sequences. Although we obtain good classification scores using CSP and SVM (66.7%), we recommend using LSTM as a preferential method of motor imagery classification because of its low computational cost due to mitigation of feature engineering and also higher accuracy, i.e., 71.2%.

While our paper emphasized the generalization capabilities of our model; however, a thorough analysis of the approach to address variation in patient demographics has not been tested. Therefore, one of the limitations of this study is that we have not evaluated the across-subject generalizability of the model, which we aim to tackle in future works. We also aim to investigate the spatial resolution aspects of brain representations and functions while also improving the current model's accuracy using the EEGMMIDB dataset. One potential approach to incorporate the spatial characteristics of recorded EEG data is using Convolutional Neural Networks (CNNs). By combining CNNs with LSTM, we can capture the spatial and temporal characteristics of EEG signals, leading to a more comprehensive understanding of the underlying brain functions.

The high accuracy achieved by the LSTM model in classifying motor imagery tasks using EEG signals holds significant potential for stroke rehabilitation. Moreover, LSTM can be effectively employed on large datasets to enhance BCI performance and improve user experience. Furthermore, the model's accuracy can be harnessed in neurofeedback training, offering real-time feedback on brain activity and motor recovery. While these findings are promising, further research and collaboration with healthcare professionals are essential to validate and translate these results into practical applications in real-world stroke rehabilitation settings. The potential impact of these advancements extends beyond stroke rehabilitation as well, as they can be adapted to other domains requiring accurate motor imagery classification, such as prosthetics, assistive devices, and virtual reality-based therapies.

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