Motor Imagery classification Based Brain Computer Interface for Rehabilitation Applications

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Abstract: This paper provides insights into the captivating field of motor imagery classification within Brain-Computer Interfaces (BCI). BCIs enable direct human-machine interaction through cognitive processes, with EEG signals decoding mental intentions with precision. Distinct EEG patterns offer valuable insights, promising intuitive BCI systems. This technology could revolutionize assistive tech, neurorehabilitation, and human-computer interaction. The paper outlines our research project, covering motor imagery experiments, data processing, and the development of EEG signal interpretation models, including feature extraction, algorithms, optimization, and rigorous testing methodologies.

Keywords: Brain computer interface, Motor Imagery, Medical Imaging, Neurorehabilitation.

1. Introduction

The primary objective of this research is to advance the field of motor imagery (MI) classification by accurately categorizing EEG data obtained from participants during cognitive tasks into specific MI task categories related to bodily movements. EEG signals, recorded through scalp electrodes, provide sequential data from multiple participants engaged in these trials [1]. The MI classification domain has witnessed significant progress, driven by innovative methodologies designed to enhance precision and efficiency.

Researchers have explored diverse techniques to address the intricacies of MI classification, such as deep domain adaptation, Bayesian convolutional neural networks, and discriminative SPD feature learning [2][3][4]. Hybrid models have also emerged, including transfer learning-based CNN and LSTM hybrids, as well as ETSNet for EEG-based temporal-spatial pattern recognition [8][9]. Additional avenues of exploration encompass multiwavelet-based sparse time-varying autoregressive modelling, multivariate variational mode decomposition, and real-time single-trial EEG analysis [10][11][12].

Recent studies have leveraged convolution, attention mechanisms, autoencoders, and channel selection to enhance MI classification accuracy [16][17][18]. In this research project, we contribute to this body of work by investigating novel methods and techniques for MI classification. Through meticulous data preprocessing, feature engineering, model development, and fine-tuning, we aim to push the boundaries of EEG-based MI classification. Our strategic allocation of data for final testing ensures the robustness and generalizability of our models, aligning with the broader goal of enhancing brain-computer interfaces (BCIs) in the context of motor imagery.

2. Dataset

Obtaining a sufficiently large and well-annotated EEG dataset for Brain-Computer Interface (BCI) research presents significant challenges due to the labor-intensive data collection process and the associated expenses [2]. For the purposes of our experimental analysis, we utilized the PhysioNet database [19], which offers a valuable resource for EEG data. The dataset is provided in EDF+ format and encompasses 64 EEG signals, each sampled at 160 samples per second, accompanied by an annotation channel.

The data collection involved subjects performing various motor and imagery tasks while utilizing the BCI2000 system. Each subject participated in 14 experimental runs, which comprised two one-minute baseline runs (one with eyes open and one with eyes closed), as well as three two-minute runs for each of the following four tasks:

1. **Fist Movement Task**: A target appeared on either the left or the right side of the screen, prompting the subject to open and close the corresponding fist until the target disappeared, followed by relaxation.
2. **Fist Movement Imagery Task**: as the previous task, a target appeared on the left or right side of the screen. However, in this case, the subject imagined opening and closing the corresponding fist until the target disappeared, followed by relaxation.
3. **Foot Movement Task**: A target emerged either at the top or bottom of the screen. The subject was instructed to open and close both fists (if the target was at the top) or both feet (if the target was at the bottom) until the target disappeared, and then relax.
4. **Foot Movement Imagery Task**: In a manner akin to the previous task, a target appeared at the top or bottom of the screen, prompting the subject to imagine

opening and closing either both fists (if the target was at the top) or both feet (if the target was at the bottom) until the target disappeared, followed by relaxation.

These tasks are summarized in Table 1 for reference and provide a rich dataset for investigating motor imagery classification within the domain of BCIs.

TABLE 1 DETAILS OF VARIOUS TASKS IN THE DATASET

Task	Subject Experiment
Task 1	open and close left or right fist
Task 2	imagine opening and closing left or right fist
Task 3	open and close both fists or both feet
Task 4	imagine opening and closing both fists or both

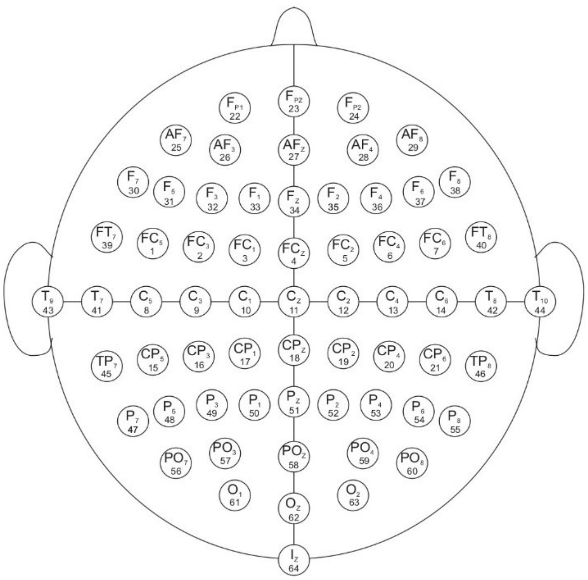

Fig. 1. EEG Electrode System 10-10

The EEG Electrode System 10-10 represents a widely accepted global standard for meticulous electrode placement during EEG recordings. This system is distinguished by its precise arrangement of electrodes at predetermined positions on the scalp, thereby ensuring consistent and reproducible measurements across individuals. The nomenclature "10-10" signifies that electrodes are situated at 10% and 20% intervals along both the anterior-posterior (AP) and right-left (RL) dimensions of the head, establishing a standardized and methodical framework for the positioning of EEG electrodes. This systematic approach enhances the reliability and comparability of EEG data acquisition across diverse research studies and participants.

3. Project Overview

In our pursuit of achieving robust motor imagery classification, our project unfolded through a series of foundational stages, each meticulously designed to enhance the effectiveness of our classification framework:

3.1 Data Collection and Preprocessing

We initiated the project by gathering motor imagery data, prioritizing data integrity through essential preprocessing steps. These steps encompassed data parsing, filtering, and resampling from 160 Hz to 128 Hz. To ensure consistency for subsequent analyses, we consolidated raw data files into a single dataset and extracted event annotations. Subsequently, we segmented the data into epochs, each spanning a 5-second window around the targeted motor imagery action, thus ensuring an equitable distribution of events.

3.2 Data Augmentation

Our data augmentation strategy introduced variability into the dataset, enriching model generalization capabilities. A key technique involved random segment trimming before and after the action period, mimicking variations in the timing of motor imagery actions. This approach provided the models with a diversified set of training examples, fortifying their robustness to cope with real-world scenarios where action timing may vary.

3.3 Model Training

We partitioned the data into training (80%) and validation (20%) sets, laying the foundation for model development. Exploring various deep learning architectures, including Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), Convolutional Neural Networks (CNN), and Deep Neural Networks (DNN), we aimed to identify the most suitable model for our task. Furthermore, hybrid models such as CNN-GRU and CNN-BiLSTM were considered to harness their potential.

3.4 Model Optimization

Concurrently, model optimization took centre stage. This phase involved fine-tuning hyperparameters and optimizing critical model parameters to improve accuracy and reduce loss. Model optimization played a pivotal role in achieving the remarkable results observed in our experiments.

3.5 Fine-Tuning

Our quest for model excellence involved exhaustive fine-tuning efforts. We systematically explored variations in learning rates, dropout rates, batch sizes, and model architectures, acknowledging their substantial influence on model performance. Employing cross-validation with varying numbers of folds ensured the robustness and reliability of our model tuning process. These rigorous fine-tuning endeavours allowed us to meticulously calibrate our models, achieving optimal performance in motor imagery classification.

3.6 Final Testing and Model Evaluation

To validate the robustness of our classification framework, we thoughtfully reserved a portion of the dataset for final testing. This step was critical to assess the models' ability to generalize effectively to unseen data. Model evaluation encompassed an array of performance metrics, including accuracy, loss, Kappa, F1 Score, Precision, and Recall.

Within this evaluation process, we conducted a comprehensive analysis of confusion matrices, shedding light on our models' proficiency in classifying motor imagery patterns. These matrices offered valuable insights into the models' capability to differentiate between distinct motor imagery tasks, guiding refinements where necessary. This in-depth analysis played a pivotal role in ensuring the reliability and effectiveness of our motor imagery classification framework.

In summary, our project journey spanned data collection, preprocessing, data augmentation, model training, model optimization, fine-tuning, final testing, and comprehensive model evaluation. Through a systematic and multifaceted approach, we aimed to advance EEG-based motor imagery classification, contributing to the broader domain of brain-computer interfaces (BCIs) and their applications in motor imagery.

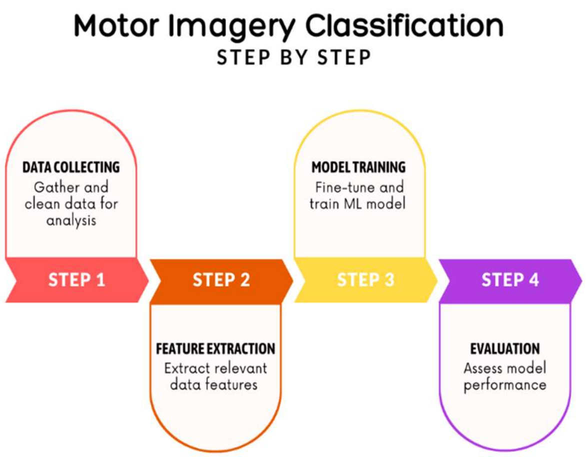

Fig. 2. Motor Imagery Classification Process

In the figure illustrating the motor imagery classification process, there are four main sequential steps:

1. Data Collection and Preprocessing: Initially, motor imagery data is collected and then subjected to preprocessing steps to clean and prepare it for analysis.
2. Feature Engineering: Subsequently, feature engineering techniques are applied to extract meaningful features from the pre-processed data. These features serve as inputs for the classification model.
3. Model Training: In the next stage, a machine learning model is trained using the engineered features. The model learns to distinguish between different motor imagery patterns.
4. Evaluation: Finally, the trained model undergoes evaluation to assess its performance and accuracy in classifying motor imagery patterns. This step ensures the reliability and effectiveness of the classification process.

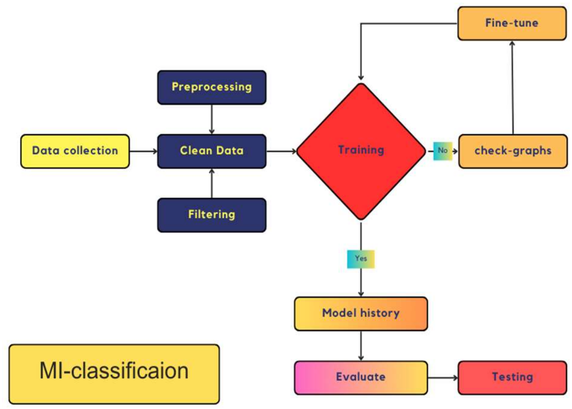

Fig. 3. Motor Imagery Classification Flowchart

- Data Collection: Gather motor imagery data.
- Preprocessing & Filtering: Clean and filter the data.
- ML Model Training: Train a machine learning model.
- Accuracy Check: Assess model performance.
- Fine-Tuning: Adjust parameters if needed.
- Retraining: Train the model again.
- High Accuracy: Achieve desired accuracy.
- Model History: Collect training history.
- Evaluation: Assess model's performance.
- Final Testing: Conduct conclusive testing.

The motor imagery classification process involves data collection, preprocessing, and filtering. Next, a machine learning model is trained, and its accuracy is checked. If the accuracy is not satisfactory, fine-tuning and retraining are performed iteratively until a high accuracy level is achieved. The model's training history is recorded, followed by evaluation and final testing steps to ensure reliable results.

4. Results and Discussion

In our pursuit of achieving robust motor imagery classification, an extensive series of experiments was conducted, encompassing a diverse array of methods and techniques. The core objective of these experiments was to accurately categorize EEG data into specific motor imagery task categories associated with bodily movements. This endeavour entailed the application of various feature engineering methodologies, rigorous model training, fine-tuning processes, and meticulous evaluation protocols.

Table 1 Algorithm Comparison for Task 1

	Kappa	F1 Score	Precision	Recall	Test Loss	Train Accuracy	Test Accuracy
LSTM	0.669	0.836	0.826	0.847	0.392	87.37 %	83.46 %
Bi-LSTM	0.643	0.828	0.831	0.81	0.455	91.45 %	**83.5 %**
CNN	0.584	0.774	0.847	0.713	0.466	81.99 %	79.25 %
CNN+GRU	0.66	0.829	0.835	0.822	0.3802	92.34 %	83.02 %

Table 2 Algorithm Comparison for Task 2

	Kappa	F1 Score	Precision	Recall	Test Loss	Train Accuracy	Test Accuracy
LSTM	0.586	0.812	0.784	0.843	0.448	83.71 %	**80.00%**
Bi-LSTM	0.584	0.811	0.787	0.835	0.491	83.50 %	79.36%
CNN	0.491	0.796	0.701	0.919	0.535	78.10 %	77.98 %
CNN+GRU	0.576	0.796	0.811	0.782	0.434	81.35 %	79.89 %

Table 3 Algorithm Comparison for Task 3

	Kappa	F1 Score	Precision	Recall	Test Loss	Train Accuracy	Test Accuracy
LSTM	0.437	0.731	0.731	0.731	0.556	77.21 %	**73.65 %**
Bi-LSTM	0.461	0.711	0.797	0.642	0.584	78.17 %	72.90 %
CNN	0.422	0.724	0.722	0.726	0.589	70.86 %	71.20 %
CNN+GRU	0.396	0.741	0.675	0.82	0.591	74.65 %	72.50 %

Table 4 Algorithm Comparison for Task 4

	Kappa	F1 Score	Precision	Recall	Test Loss	Train Accuracy	Test Accuracy
LSTM	0.421	0.711	0.709	0.681	0.571	74.67 %	71.78 %
Bi-LSTM	0.432	0.722	0.699	0.742	0.555	78.21 %	**72.83 %**
CNN	0.337	0.691	0.638	0.753	0.619	69.99 %	67.02 %
CNN+GRU	0.424	0.701	0.721	0.683	0.578	70.57 %	71.25 %

Tables 2 through 5 provide a comprehensive comparative analysis of the algorithms employed across different motor imagery tasks. These tables offer a detailed exposition of performance metrics, including Kappa, F1 Score, Precision, Recall, Test Loss, Train Accuracy, and Test Accuracy. The systematic evaluation of diverse models and methodologies has yielded invaluable insights into the efficacy of motor imagery classification techniques, further enhancing our understanding of this critical aspect of our research.

4.1. Effectiveness of Feature Engineering

The experiments demonstrated that the incorporation of feature engineering techniques significantly improved the classification accuracy across all tasks. The carefully crafted feature extraction methods enhanced the models' ability to distinguish between different motor imagery patterns.

4.2. Improved Test Accuracy

When compared with results obtained without feature engineering, it is evident that the application of feature engineering consistently led to higher test accuracy levels in all tasks. This underscores the importance of preprocessing and feature extraction in EEG-based motor imagery classification.

4.3 Optimal Models

Among the models tested, the Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM) consistently exhibited the highest test accuracy. These models leveraged their ability to capture sequential patterns in EEG data, showcasing their suitability for motor imagery classification tasks. It's worth noting that these models were trained using the Adam optimizer with a learning rate of 0.0005 and employed binary cross-entropy as the loss function. This configuration played a crucial role in achieving the remarkable performance observed in the results.

4.4 Generalizability and Robustness

To ensure the robustness of the classification framework, a strategic portion of the dataset was reserved for final testing. The results indicated that the developed models could generalize well to unseen data, reaffirming their potential for real-world applications.

4.5 Continuous Improvement

It's important to note that the fine-tuning process played a pivotal role in achieving the desired accuracy levels. Through iterative adjustments of model parameters, the learning curves exhibited increasing accuracy and decreasing loss, highlighting the importance of model optimization.

Limitations and Challenges

4 **Data Quality and Quantity:** The study faced limitations related to the quality and quantity of EEG data. Some data contained artifacts and noise, which posed challenges in achieving accurate classification. Additionally, having access to a larger dataset could have potentially improve model performance.

5 **Feature Engineering:** Challenges were encountered during the feature engineering process. Implementing specific feature extraction techniques proved to be complex, and there were computational constraints in handling extensive feature sets.

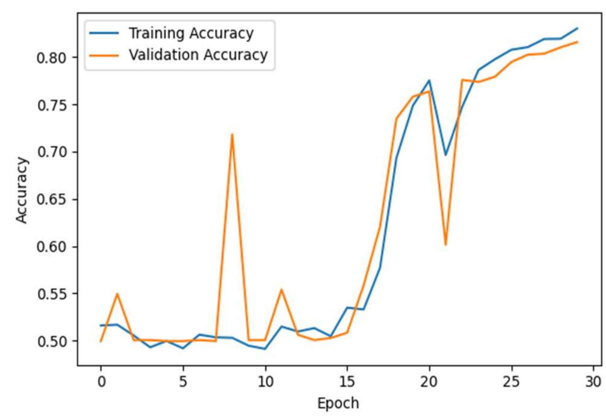

Fig. 4. Accuracy Evolution - Bi-LSTM model (Task 1)

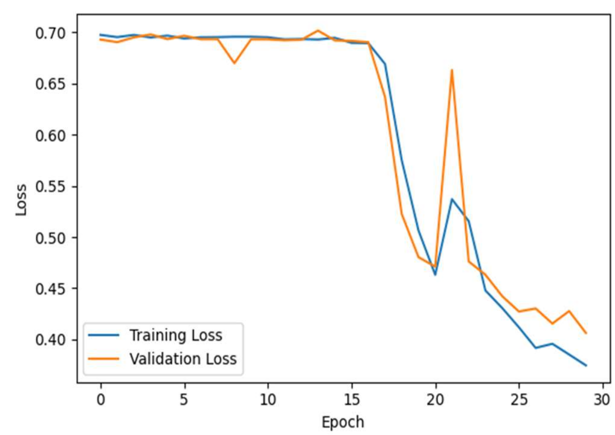

Fig. 5. Loss progression - Bi-LSTM model (Task 1)

The first graph displays rising accuracy as the Bi-LSTM model classifies Task 1 motor imagery patterns, while the second graph shows decreasing loss, indicating improved performance.

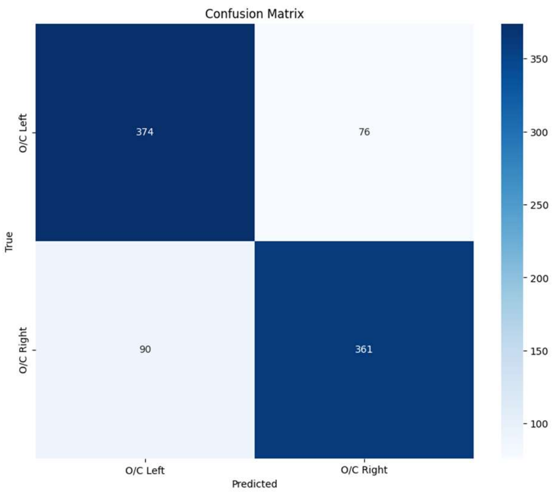

Fig. 6. Confusion Matrix - Bi-LSTM model (Task 1)

The confusion matrix shown in figure 5 provides visual insights into classification accuracy of Bi-LSTM model for task 1.

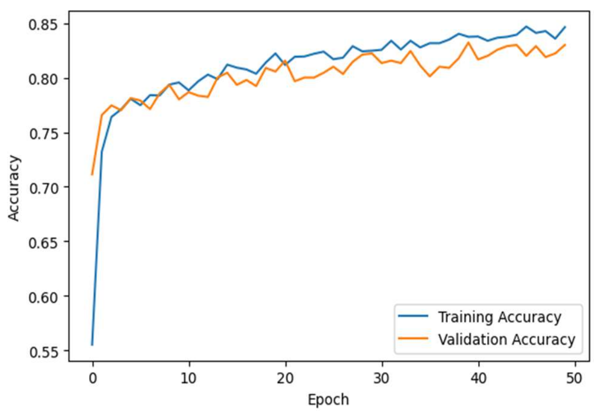

Fig. 7. Accuracy Evolution - CNN-GRU model (Task 1)

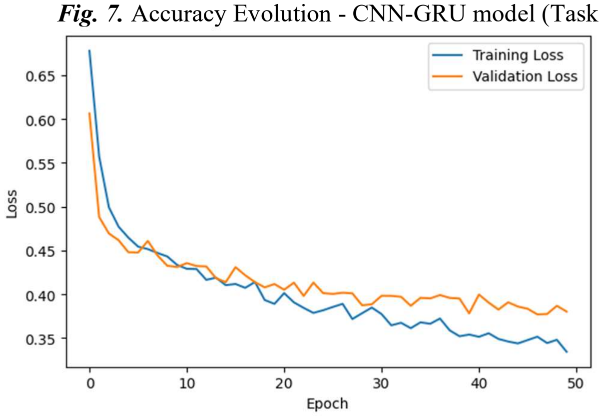

Fig. 8. Loss progression - CNN-GRU model (Task 1)

The first graph illustrates the progressive accuracy improvement of the CNN+GRU model during Task 1 motor imagery classification training. In contrast, the second graph depicts the diminishing loss as the model learns to classify Task 1 patterns, signifying enhanced performance over time.

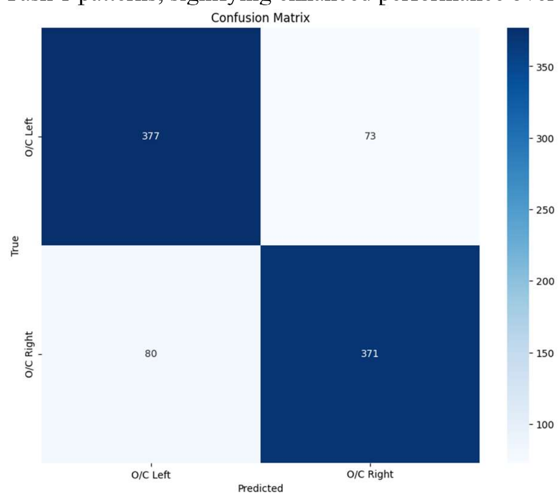

Fig. 9. Confusion Matrix - CNN-GRU model (Task 1)

The confusion matrix shown in figure 7 provides visual insights into classification accuracy of CNN+GRU model for task 1.

6 Conclusion

In the pursuit of advancing motor imagery classification within Brain-Computer Interfaces (BCIs), this research embarked on a comprehensive exploration. Through a series of meticulous experiments and analyses, we have gained valuable insights into the realm of EEG-based motor imagery classification.

Our experiments encompassed the application of a wide array of models, from traditional LSTM to advanced hybrid models such as CNN+GRU and Bi-LSTM-CNN. These endeavours highlighted the significance of model selection in EEG-based motor imagery classification. Notably, we achieved the highest test accuracy with LSTM and Bi-LSTM models, underscoring their effectiveness in this context.

The integration of feature engineering into our workflow yielded promising results, consistently outperforming models trained without feature engineering. These findings reinforce the importance of data preprocessing and feature extraction in enhancing classification accuracy within the motor imagery classification domain.

Additionally, the challenges faced during this research, including data acquisition limitations, underscore the complexities inherent in EEG data collection and the need for standardized datasets to foster further research and development.

As we conclude this report, it is evident that the journey to harness the potential of motor imagery classification is ongoing. This research contributes to the existing body of knowledge in EEG-based BCIs and motor imagery classification, paving the way for future innovations in assistive technology, neurorehabilitation, and human-computer interaction.

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