Deep Learning for EEG-Based Motor Imagery Classification: Towards Enhanced Human-Machine Interaction and Assistive Robotics

Nejia Boutarfaia[1], Samuele Russo[2], Ahmed Tibermacine[1] and Imad Eddine Tibermacine[3]

[1]Department of Computer Science, University Mohamed Khider of Biskra, Algeria

[2]Department of Psychology, Sapienza University of Rome, Italy

[3]Department of Computer, Control and Management Engineering, Sapienza University of Rome, Italy

Abstract

This study presents a comprehensive exploration of EEG-based motor imagery classification using advanced deep learning architectures. Focusing on six distinct motor imagery classes, we investigate the performance of convolutional neural networks (CNN), CNN with Long Short-Term Memory (CNN-LSTM), and CNN with Bidirectional LSTM (CNN-BILSTM) models. The CNN architecture excels with a remarkable accuracy of 99.86%, while the CNN-LSTM and CNN-BILSTM models achieve 98.39% and 99.27%, respectively, showcasing their effectiveness in decoding EEG signals associated with imagined movements.The results underscore the potential applications of this research in fields such as assistive robotics and automation, showcasing the ability to translate cognitive intent into robotic actions. This study offers valuable insights into the realm of deep learning for EEG analysis, setting the stage for advancements in brain-computer interfaces and human-machine interaction.

Keywords

Electroencephalogram (EEG), Deep Learning, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Bidirectional LSTM (BILSTM), Motor Imagery, Brain-Computer Interface (BCI)

1. Introduction

Using deep learning for EEG signal classification has applications in the brain. The advancement of brain-controlled robots capable of direct communication with humans is beneficial in several scenarios. A brain-computer interface (BCI) system is vital in offering additional communication between the human brain and other outside entities, such as robots[1]. BCI becomes a tool for determining the goals of people dealing with medical situations by examining recorded brain signals and interpreting neural responses. Its main goal is to provide these people the ability to carry out motor functions, which will help them achieve a greater quality of life[2, 3, 4].

For individuals dealing with medical issues, it becomes a lifeline. A BCI is a computer-based communication system designed to analyze signals originating from the neural activity within the central nervous system[5, 6].

BCI systems are categorized into exogenous and endogenous types. Exogenous BCIs rely on external stimuli to evoke specific brain responses, with electroencephalogram (EEG) patterns such as P300 and steady-state visual evoked potentials (SSVEP) being typical examples[7]. These systems are stable, require less training, but depend on external cues and may cause user fatigue. In contrast, endogenous BCIs, also known as active BCIs, are based on self-regulation of brain rhythms, specifically motor imagery (MI), reflecting the user's autonomous intentions without external stimulation. MI induces event-related desynchronization/synchronization (ERD/ERS) in the brain's motor area, allowing absolute mind control. While active BCIs do not rely on external stimuli and offer more direct user modulation, they require specific attention and have gained attention for their potential in realizing genuine user-controlled interfaces[8, 9**?**].

In neuroscience and brain-computer interfaces (BCI), motor imagery (MI) refers to the cognitive process in which humans mentally simulate or observe a motor activity, such as the movement of a limb or the execution of a particular task, without any accompanying physical motion [8]. Mentally rehearsing actions activates the same brain pathways as executing those movements. In brain-computer interfaces (BCI), electroencephalogram (EEG) data are commonly used to collect and analyze brain activity related to motor imagery. By analyzing brain activity patterns during motor imagery (MI), researchers can decode the intended motor motions and convert them into control signals for external devices[10].

In recent years, deep learning techniques have redefined the landscape of MI classification, offering unprecedented capabilities in extracting complex patterns and

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nejia.boutarfaia@univ-biskra.dz (N. Boutarfaia); samuele.russo@uniroma1.it (S. Russo); ahmed.tibermacine@univ-biskra.dz (A. Tibermacine); tibermacine@diag.uniroma1.it (I. E. Tibermacine)

representations from EEG data [11][12]. Its end-to-end methodology sets deep learning apart, eliminating the need for manual feature extraction methods. Instead, it autonomously learns many essential parameters and identifies valuable information within the data[13].

Various advanced deep-learning techniques were utilized to improve Motor Imagery's (MI) precision. As an example, in this study [14] explores the implementation of a convolutional neural network (CNN) architecture with a single convolutional layer for the classification of motor imagery (MI) tasks based on electroencephalogram (EEG) signals. The designed CNN model includes a convolutional layer, ReLU activation, and max-pooling. The output layer is configured with either 2 or 4 nodes, depending on the specific number of classes in the MI classification task. The document highlights incorporating data augmentation techniques and utilizing common spatial patterns (CSP) for effective feature extraction. Results from the proposed approach demonstrate promising outcomes in both two-class and four-class MI classification scenarios.

In Ref [15], The authors propose a new approach that combines continuous wavelet transform (CWT) with a simplified convolutional neural network (SCNN) to enhance the recognition accuracy of Motor Imagery (MI) electroencephalogram (EEG) signals. The CWT is applied to map MI-EEG signals into time-frequency image signals, which are then input into the SCNN for feature extraction and classification.

In addition, several research has investigated different methods, such as Long Short-Term Memory (LSTM), which have shown good results in motor imagery classification using EEG. In light of promising findings, one study [16] introduces an EEG classification framework for motor imagery tasks in BCI systems. The framework leverages LSTM networks, incorporates a one-dimensional aggregate approximation (1d-AX) for signal representation, and employs a channel weighting technique inspired by common spatial patterns to boost effectiveness. In reference [17], they combine a one-dimensional convolutional neural network (1D CNN) with long short-term memory (LSTM)[18]. The suggested deep learning network improves classification accuracy by using CNN and LSTM to extract temporal representations of MI tasks successfully[19]. The preprocessing of EEG data encompasses band-pass filtering and data augmentation using a sliding window. The CNN captures essential time domain features, and the subsequent LSTM facilitates additional feature extraction, culminating in a robust classifier designed for four MI tasks[20].

Many research utilize BiLSTM as an excellent case study. This research [21] introduces a novel approach for decoding imagined finger motions using MI-EEG data. The approach effectively tackles noise challenges in small, noisy signals using Empirical Mode Decomposition (EMD) and a Stacked BiLSTM architecture. The method demonstrates notable success, achieving an accuracy of 82.26% on a widely used dataset. The research offers an innovative decoding approach and effective noise reduction through EMD, explicitly enhancing the classification of MI-EEG signals associated with right-hand finger movements[22].

Numerous advanced deep-learning methodologies have been employed to enhance the accuracy of motor imagery classification within Brain-Computer Interfaces (BCIs). This motivates us to explore innovative strategies for motor imagery (MI) classification, contributing to the continuous progress in the domain. MI, a cognitive process involving mental simulation of movements without physical execution, holds significance in brain-computer interface (BCI) research. In this investigation, we focus on a specific subset of six classes from the EEG dataset, specifically addressing tasks associated with motor imagery actions. Our aim is to evaluate the appropriateness of these classes for efficient EEG-based classification, ultimately aiming to facilitate intuitive and precise control of robotic systems.

2. Materials and Methods

2.1. Dataset

The dataset utilized in our study, attributed to Gerwin Schalk and colleagues [23], is a pivotal asset in Brain-Computer Interface (BCI) research.

Obtained from over 1500 EEG recordings with the participation of 109 volunteers, the dataset offers a comprehensive data collection. The experiments, facilitated by the BCI2000 system, involve various motor/imagery tasks and baseline measurements.

Electrode placement follows the international 10-10 system. At the same time, detailed information about the dataset is accessible through the original publication on PhysioBank. The participants completed a total of 14 experimental trials, as outlined in Figure 1, which provides a detailed description of the experiment. Each trial comprised two one-minute initial sessions—one with eyes open and another with eyes closed—and three two-minute trials for each of the four specified tasks.

While the original dataset contains continuous multichannel data with a substantial number of users in our study, we concentrated on the EEG signals obtained from a subset of seven subjects selected randomly. Specifically, our focus was on tasks related to imagined movements, namely tasks 4, 6, 8, 10, 12, and 14. Tasks 4, 8, and 12 involve imagined movements associated with both the right and left fists, as well as periods of relaxation. On the other hand, tasks 6, 10, and 14 involve imagined movements of both fists and both feet.

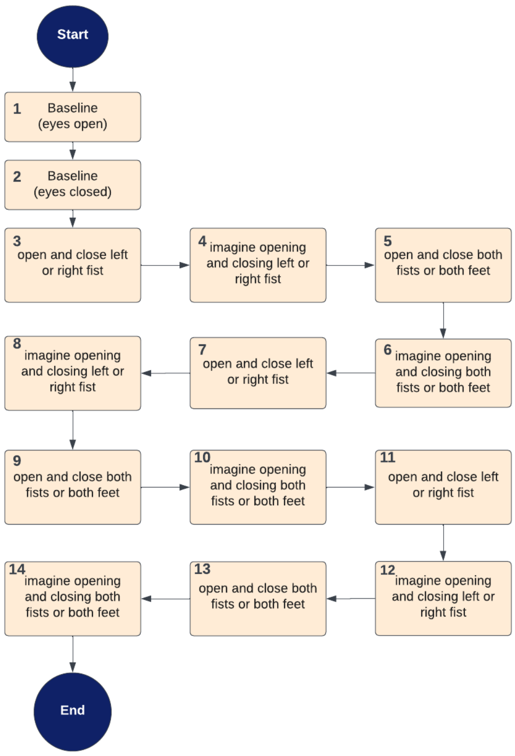

Figure 1: Overview of the 14-trial EEG experiment.

2.2. Convolutional Neural Networks (CNN)

CNNs are very good at classifying images because they use neural layers to learn hierarchically organized features. People are now interested in making CNNs use data that isn't pictures, like time-series data. CNNs are a great way to get features from EEG data and recognize patterns. This is because they can show how electrodes are spread out in space and how brain activity changes over time [24, 25]. Convolutional layers, pooling layers, activation functions, and fully connected layers are the main parts that make up a CNN. To make output feature maps, convolutional layers use convolutional kernels to run convolutions. At the same time, pooling layers subsample feature maps while keeping the most essential characteristics. Adding activation functions like Sigmoid, Tanh, and ReLU to the network creates non-linearity, a vital part of matching inputs to outputs correctly.

Sigmoid function:

$$\mathrm{Sigmoid}(x) = \frac{1}{1+e^{-x}} \tag{1}$$

Tanh function:

$$\mathrm{Tanh}(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{2}$$

ReLU function:

$$\mathrm{ReLU}(x) = \max(0, x) \tag{3}$$

In the design of a CNN, the final layers play a crucial role in handling classification tasks. These layers, known as fully connected layers, establish connections between every neuron within a layer and those from its preceding layer. The ultimate layer of fully connected layers serves as the output layer, functioning as the classifier in the CNN architecture.

2.3. Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM)

LSTM designed to overcome the vanishing gradient problem in traditional RNNs, introduces memory cells with gating mechanisms, including input, forget, and output gates, to control the flow of information. It comprises a cell state representing long-term memory and a hidden state representing short-term memory or output [26].

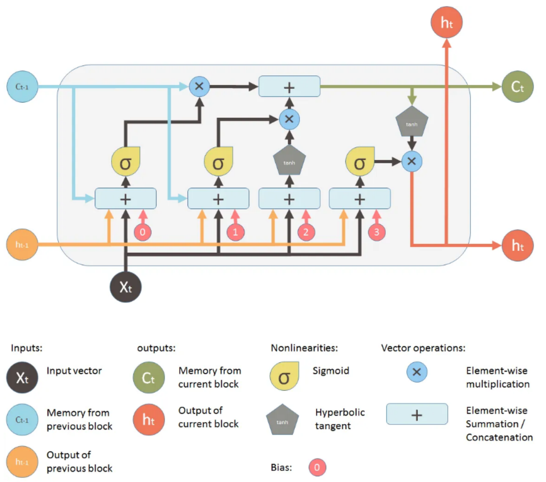

Figure 2: The architecture of a LSTM model [27].

Bidirectional Long Short-Term Memory (Bi-LSTM) is an extension of the traditional LSTM, a type of recurrent neural network (RNN). LSTMs are adept at capturing and retaining long-term dependencies in sequential data, making them suitable for applications like natural language processing, time series prediction, and speech recognition [28].

The term "bidirectional" in Bi-LSTM refers to the fact that it processes input sequences in both forward and

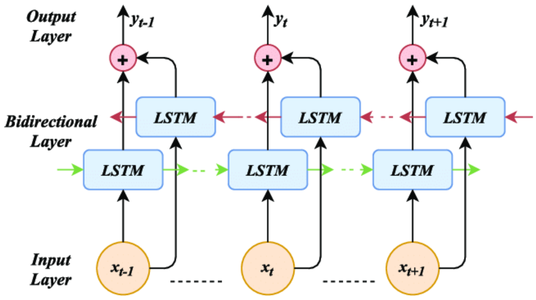

Figure 3: Bidirectional LSTM model showing the input and output layers. The red arrows represent the backward sequence track and green the forward sequence track [29].

backward directions. This bidirectional processing helps the network capture information from both the past and the future of a given time step, allowing it to better understand the context and dependencies in the sequence. The Bi-LSTM architecture consists of two LSTM layers, one that processes the input sequence in the forward direction and another in the backward direction. The results from both directions are often combined before passing them on to the next layer or used for the final prediction[28, 30].

2.4. Proposed Architecture

The dataset is subjected to a preprocessing phase that includes applying an 8–30 Hz filter and a notch filter, followed by sampling at a frequency of 125 Hz. This essential preprocessing step refines the raw EEG signals, effectively eliminating undesirable frequency components and ensuring the data's suitability for further analysis. The 8–30 Hz filter is instrumental in concentrating on pertinent frequency bands linked to neural activity, while the notch filter serves to eliminate specific unwanted frequencies, such as those associated with power line interference.

The CNN architecture, comprising Conv1D, Batch Normalization, MaxPooling1D, Dropout, Flatten, and Dense layers, demonstrates effectiveness in classifying EEG data across 6 classes. The CNN with Long Short-Term Memory (CNN-LSTM) model seamlessly integrates CNN and LSTM layers to capture spatial and temporal features. This architecture includes CNN, Batch Normalization, MaxPooling1D, Dropout, LSTM, Flatten, and Dense layers, showcasing commendable accuracy in EEG data classification by skillfully combining spatial and temporal aspects. The CNN with Bidirectional LSTM (CNN-BiLSTM) architecture enhances EEG data classification by combining CNN and Bidirectional LSTM networks. The model incorporates CNN, Batch Normalization, MaxPooling1D, Dropout, Bidirectional LSTM, Dropout, Flatten, and Dense layers. This hybrid approach synergizes the strengths of CNN for spatial features and Bidirectional LSTM for temporal dependencies, resulting in a robust classification model.

A five-fold stratified k-fold cross-validation is implemented using the StratifiedKFold function from scikit-learn. The dataset is divided into training and testing sets for each fold, and each model is compiled with categorical cross-entropy, Adam optimizer, and accuracy as the metric. The training spans 100 epochs with a batch size of 32, facilitating a thorough assessment of the model's performance across diverse data subsets.

3. Results

To assess the performance of the three models, we employed key scoring metrics, including Accuracy, Recall, Precision, and F1-Score. These metrics provide a comprehensive evaluation of the models' effectiveness in handling classification tasks. Each sign gives a different view of different parts of a model's effectiveness, and when mixed, they provide a complete visualization:

$$\text{Precision} = \frac{\text{TP}}{\text{TP + FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP + FN}}$$

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision + Recall}}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

where TP are the true positives, FP the false positives, TN the true negatives, and FN the false negatives.

Table 1
Comparison of Architectures.

Architecture	Precision	Recall	F1	**Accuracy**
CNN	1.00	1.00	1.00	**99.86%**
CNN-LSTM	0.98	0.98	0.98	**98.39%**
CNN-BILSTM	1.00	0.99	0.99	**99.27%**

The CNN architecture showcased exceptional performance, achieving perfect precision, recall, and F1-Score, leading to an impressive overall accuracy of 99.86%. This underscores the model's effectiveness in accurately classifying EEG data. The CNN-LSTM model, although slightly less accurate, still demonstrated commendable results, with precision, recall, and F1-Score values at 0.98

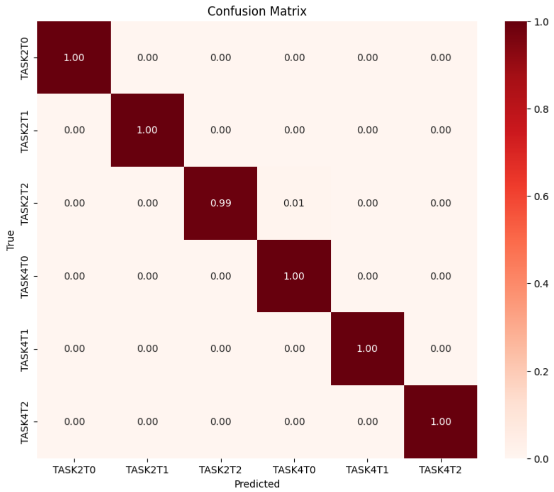

Figure 4: Confusion matrix for the proposed CNN model.

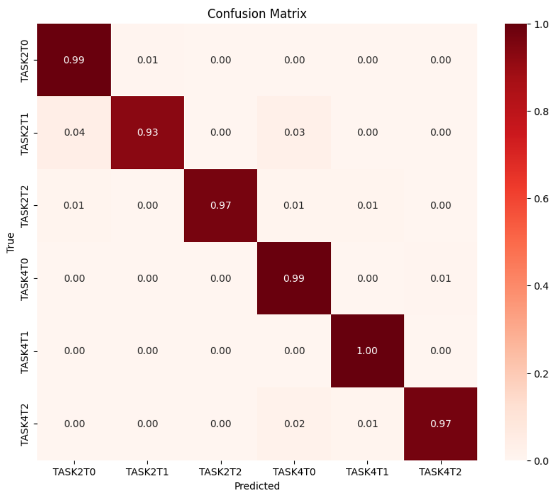

Figure 5: Confusion matrix for the proposed CNN-LSTM model.

and an overall accuracy of 98.39%. This model effectively combines spatial and temporal features for EEG classification, emphasizing a balance between complexity and accuracy. The CNN-BILSTM architecture displayed a well-rounded performance, with precision, recall, and F1-Score all reaching 1, 0.99, and 0.99, respectively. Combining CNN for spatial features and Bidirectional LSTM for temporal dependencies, this hybrid approach achieved an accuracy of 99.27%, highlighting its efficacy in accurate EEG data classification.

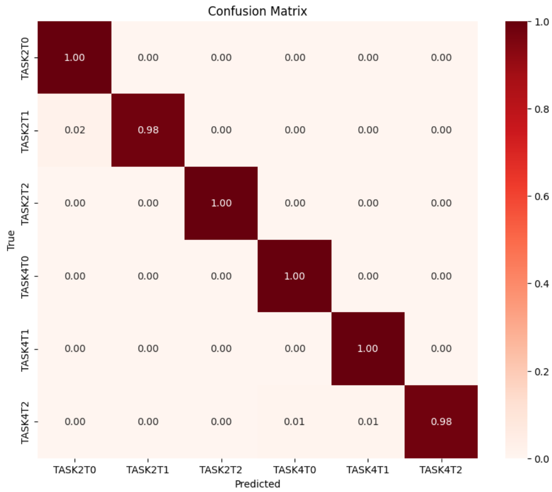

Figure 6: Confusion matrix for the proposed CNN-BILSTM model.

4. Discussion

The evaluation results of three distinct architectures, namely CNN, CNN-LSTM, and CNN-BILSTM, shed light on their respective performances in classifying EEG data with 6 classes. The CNN model exhibits exceptional performance across all metrics. It achieves precision, recall, and an F1-score of 1.00 for most classes, highlighting its ability to classify each class accurately. The overall accuracy of 99.86% underscores the model's effectiveness in capturing intricate patterns within the EEG data. The precision-recall curves for each class demonstrate the model's robustness and reliability. The CNN-LSTM model, incorporating both convolutional and long short-term memory layers, displays a commendable performance but with a slight decrease in precision, recall, and F1-score compared to the pure CNN model. This suggests a potential trade-off between model complexity and overall performance. The accuracy of 98.39% indicates reliable classification, though less than the CNN architecture. The CNN-BILSTM model, combining the strengths of CNN and Bidirectional LSTM, provides an excellent balance between precision, recall, and F1-score. With precision above 1 for most classes and an accuracy of 99.27%, it demonstrates the model's ability to capture both spatial and temporal dependencies in the EEG data. The bidirectional processing contributes to understanding the context and dependencies in the sequence.

The outcomes obtained from the implemented models indicate their proficiency in recognizing patterns and extracting features from EEG data, resulting in successful classification. This underscores the appropriateness and effectiveness of the selected models for the specific EEG signal classification task. The models' capability to discern complex neural patterns contributes significantly to the overall success of the classification process, offering valuable implications for applications in neuroscientific research and brain-computer interface systems.

The focused analysis on a subset of six classes derived from motor imagery tasks opens up intriguing possibilities for the practical deployment of brain-computer interface (BCI) technologies in the field of robot navigation. Consider a scenario where a user, equipped with an EEG-based BCI system, intends to control a robot's movements seamlessly. In this scenario, the selected six classes correspond to distinct motor imagery actions with direct relevance to robot navigation commands: closing and opening the left hand for turning left, closing and opening the right hand for turning right, and simultaneously closing and opening both fists and both feet for stopping and moving forward, respectively. This subset aligns with intuitive and fundamental commands essential for controlling the robot's spatial movements.

Table 2
Mapping Between Movements and Commands for Robotic Control.

Real or Imagined Movement	Corresponding Commands
Closing/opening left hand	**Turning left**
Closing/opening right hand	**Turning right**
Opening/closing both fists	**Stopping**
Opening/closing both feet	**Going forward**

As the user engages in motor imagery actions, the EEG signals associated with the specific classes are decoded in real-time by the implemented classification models. The system translates these decoded signals into corresponding robot commands, enabling the user to navigate the robot effortlessly. For instance, by simply imagining the closure of the left hand, the robot seamlessly executes a left turn, offering an intuitive and natural interaction mechanism.

However, challenges and considerations arise in the implementation of such a scenario. Real-time processing, user adaptation to the BCI system, and robustness in various environmental conditions are factors that require careful attention. The user's cognitive load, comfort, and the need for continuous improvement in the classification models become focal points for refinement.

Despite these challenges, the envisioned scenario highlights the potential transformative impact of motor imagery classification in robot navigation. The seamless fusion of cognitive intent and robotic action could revolutionize human-robot interaction, paving the way for intuitive and accessible control mechanisms in diverse applications, ranging from assistive robotics to smart home automation.

The scenario encourages future exploration into refining the proposed approach, addressing practical challenges, and expanding its applicability in real-world settings. This discussion signals a step toward unlocking the full potential of BCIs in enhancing the synergy between human cognition and robotic systems.

5. Conclusions

This study advances EEG-based motor imagery classification, evaluating CNN, CNN-LSTM, and CNN-BILSTM models for six selected classes. Results demonstrate exceptional accuracy (CNN: 99.86%, CNN-LSTM: 98.39%, CNN-BILSTM: 99.27%). The discussion introduces a compelling scenario, envisioning the practical application of the six selected classes in robot navigation through brain-computer interface technology. This scenario exemplifies the potential real-world impact of motor imagery classification, providing a seamless link between cognitive intent and robotic actions. Despite successes, challenges in real-time processing and model robustness persist. The study encourages further refinement and addresses practical considerations for broader implementation. The findings contribute to the field, shaping the future of human-machine interaction, particularly in assistive robotics and intelligent automation.

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