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NeuNet: A Next-Gen Framework for Motor Imagery Recognition Leveraging Attention-Based CNN-BiLSTM

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Brain Computer Interaction (BCI), Motor Imagery (MI) signals, Electroencephalogram (EEG), Convolution neural network (CNN), Bi-directional long-short term memory (Bi-LSTM).

ABSTRACT

Categorization of motor imagery (MI) using electroencephalogram (EEG) signals is a critical component of brain-computer interface (BCI) systems to assist communication and control tasks for people with motor impairment. Classification is not trivial due to the highly complex and a non- stationary characteristic of EEG signals. The present paper has proposed a hybrid model of deep learning process entitled as NeuNet that combines Convolutional Neural Networks (CNN), Bi-directional Long Short-Term Memory (BiLSTM), and attention strategy to classify MI using EEG signals. The CNN layers introduced here to extract the spatial features of EEG signals from the raw dataset, while the BiLSTM layers were capable of learning temporal features in both forward and backward direction. Moreover, the attention mechanism learnt how to attend to the most informative time steps, allowing the model to learn the whitening factors of discriminative patterns. The hybrid model was tested on an EEG dataset collected from the scalp of the subjects imagining four motor movement directions (such as left, right, forward, and backward) using a 32-channel NUROMAX PVT. LTD, Medicaid Systems, with gold cup electrodes placed according to the 10-20 electrode placement strategy. The EEG MI dataset, resulting an improved classification accuracy and generalization capability to continuous BCI tasks in comparison to traditional deep learning methods. The experimental results demonstrated the attention- based CNN-BiLSTM model architecture was effective at addressing the spatiotemporal characteristics of EEG signals, which can be beneficial for online BCI applications.

1. INTRODUCTION

Brain Computer Interaction (BCI) systems allow for direct pathways without the need for muscle activity facilitated by external devices, allowing running applications without physically moving [1]. Motor imagery (MI) classification is a way of BCI that is widely studied. In this type of approach, individuals would imagine different actions would be taking place (e.g., imagining moving the left or right hand) that created distinguishable differences in patterns found in a standard electroencephalogram (EEG) signal [2]. Once the movements or actions are correctly imagined, these can be respectively decoded and captured to create control commands for assistive technology devices, like robotic prosthetics, wheelchairs, and speech generating devices.

Despite the promise of EEG-based MI classification, it remains very difficult. The challenges include a lower consumption of signal-to-noise ratio (SNR), the non-stationary feature of EEG signals and individual differences both within each subject (e.g., day to day) and across subjects. The need for classifying between two or more classes using data that was determined via connections established through computed models makes it difficult to gain properly constructed and reliable data sets [3]. Traditional machine learning models not only require tasks before using the modelling to establish manual features within the EEG data, but they still have shallow machine representations and are often incapable of expressing more complex task-related structures into a non-linear structure from normal EEG data. Consequently, feature extraction and developing a robust classifier remaining two of the most challenging areas of research.

In recent years, deep learning models are capable of learning more robust and detailed representations directly from raw EEG signals without requiring any manual feature extraction. The field of deep learning-based motor imagery (MI) EEG classification has progressed rapidly, mainly due to the introduction of new models and learning paradigms [4]. For instance, attention-based models have emerged, as with CNN-LSTM models that include temporal attention, to focus on the relevant pieces of information for improved accuracy. Transformer-based methods have also emerged for capturing and connecting long-range information to perform inference without recurrence. In addition, Graph Neural Networks (GNNs) [5] and other multi-channel models have been proposed to better utilize the shared spatial relationships of EEG channels. Domain adaptation and transfer learning, which contribute to solving inter-subject variability, have enabled improved generalization across subjects [6]. Finally, compact CNNs are being developed to enable real-time inference on small form factor BCI devices, and multi-modal approaches combine EEG with other physiological signals yielding the potential for additional robustness [7]. Overall, these approaches embody an evolution towards improved accuracy, generalizability, and practicality in BCI and MI EEG classification.

This research investigates deep learning methods that consist of CNN, Bi-LSTM models along with the attention mechanism in classifying MI signals [8]. The proposed architecture of the classifier design uses CNNs to extract spatial features from multichannel EEG data, and uses two direction Bi-LSTMs to capture temporal dependencies of the EEG features in both forward and backward directions. The attention algorithm allows the networks to attend to the most informative time steps of the EEG signal and in turn improve performance and interpretation.

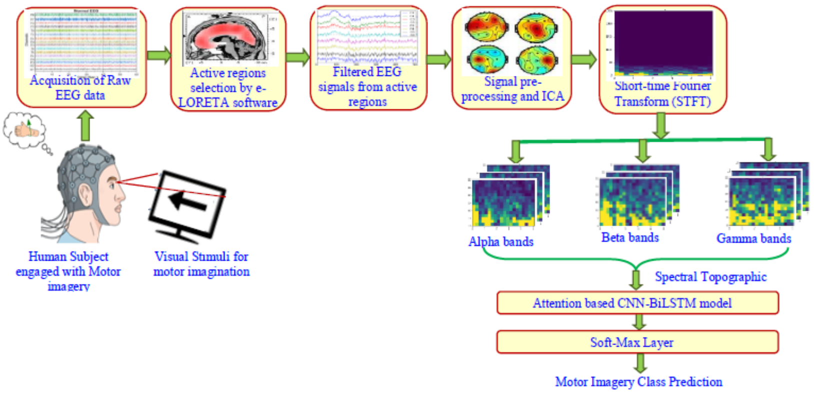

Fig. 1 Overall framework of Motor Imagery signals using Attention based CNN-BiLSTM model

To assess the performance effectiveness of the NeuNet model, experiments are conducted on an EEG dataset collected by 32-channel NUROMAX PVT. LTD, Medicaid Systems, in which participants completed motor imagery (MI) tasks of four imagined directions: left, right, forward, and backward. To investigate the brain activation patterns associated with the MI signals, exact Low Resolution Topographic Analysis (e-LORETA) software is employed to indicate the most activation in motor cortex and frontal areas during the cognitive tasks.

The key objective of NeuNet is to present EEG time-series data in a 2Dimentional multispectral format while minimizing the loss of significant information. This paper proposes a unique approach to transforming EEG time-series data into 2D images using appropriate projections and interpolations. The 2D images are processed using CNN network to extract detailed spatial (frequency domain) characteristics. The original EEG time-series data are processed in a separate network using an attention-based Bidirectional LSTM model to learn the relavent temporal dependencies of interest. Finally, spatial and temporal features are merged from both networks to enhance classification performance. The findings indicate that the attention-based CNN-BiLSTM model surpasses traditional methods and baseline deep learning methods with respect to classification performance and generalize ability. Therefore, the attention-based CNN-BiLSTM model has the potential to be a viable solution for real-time and continuous BCI applications.

This article is organized into five segmentations. Section II delivers a comprehensive overview of the motor imagery classification system. Section III demonstrates the structure of NeuNet. Section IV presents the experimental steps and results used to analyze the performance of the classifier proposed here. Performance of the classifier and its statistical validation were conducted in section IV. The conclusions are stated in Section V.

2. OVERALL SYSTEM FRAMEWORK

This segment focus on the classification of four motor imagery signals namely left, right, forward, and backward based on the brain responses of the subject during the cognitive task. The overall system design of the proposed model is depicted in Fig. 1. The first step of the system is to capture the electroencephalograms (EEG) signals when the subjects perform motor imagery (MI) tasks. Gold cup electrodes are placed on the scalp where brain activity is recorded as subjects imagine motor movement in four distinct directions; left, right, forward, and backward. All processing and analysis will be based on these raw EEG signals. Once the signals are acquired, Exact Low Resolution Brain Electromagnetic Topographic Analysis (e-LORETA) is deployed to examine the cortical activation patterns associated with the MI tasks. E-LORETA is a proper localization technique, locating brain activity and measuring where the maximum activation occurred in the brain for each MI tasks, specifically the motor cortex in conjunction with the frontal areas [9]. The limitations of EEG spatial resolution are exacerbated to an extent. However, e-LORETA enhances our interpretability of the EEG results by providing reasonably accurately estimates of the cortical activation topography, which will help us to assess what signals, are most relevant for our further processing. EEG signals from the awake naive experience corresponding to activated cortical regions indicated by e-LORETA software were pre- processed using a 10th-order elliptical band-pass filter (5-35 Hz) to remove artifacts and physiological noise [10]. To separate sources and eliminate redundancy, Independent Component Analysis (ICA) was performed to separate the EEG signals into 19 independent components [11]. This decomposition not only facilitated the neural sources separation but also removes redundancies and improves the quality of the features extracted from the signals. The pre- processed EEG signals are then converted into a time– frequency domain representation using the Short-time Fourier Transform (STFT) [12]. The results are two-dimensional spectrograms, in which the EEG time-series data has been converted into the frequency domain. Spectrograms provide a dynamic power distribution of the signals over time and frequency, offering another rich feature representation for classification. Eventually, the spectrograms are input into a CNN model for spatial feature extraction. The CNN learns the discriminative patterns embedded in the spectrograms and these patterns function as high-level features to differentiate each of the four motor imagery classes. The features are then processed at the classification stage, as described in Section III

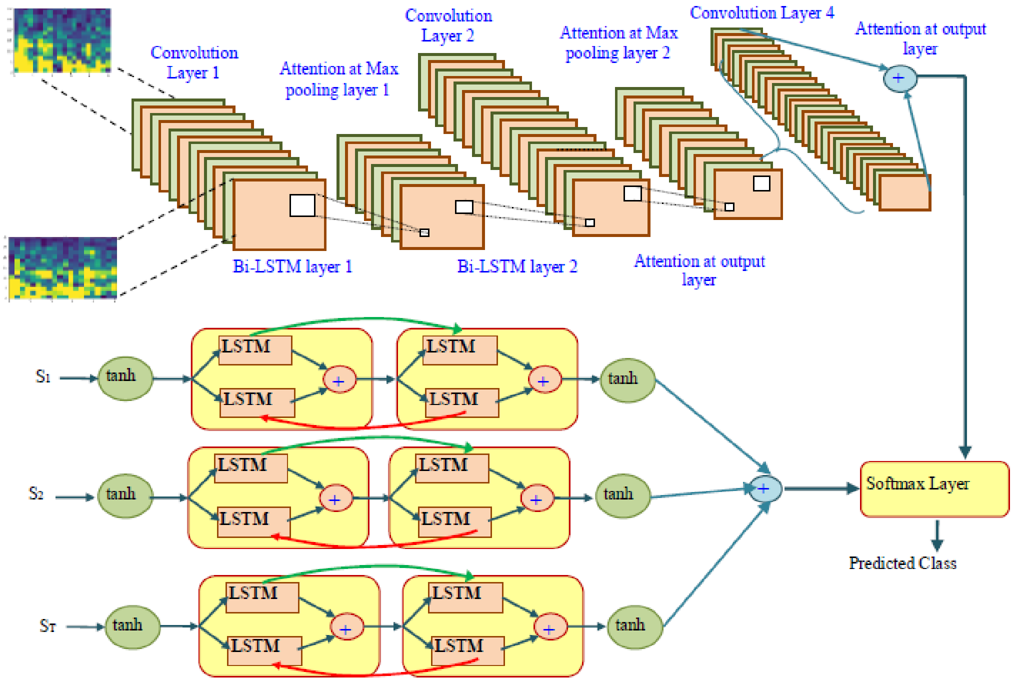

Fig. 2. System Architecture of the proposed Attention based Convolution Bi-Long short term Memory (ACNN-BiLSTM) model

3. ARCHITECTURE OF PROPOSED ATTENTION BASED CNN BI-LSTM MODEL

This section describes the classification of motor imagery signals (Depicted in Fig. 2). The model mainly engages with CNN to extract the spatial features, and includes a Bi-LSTM network to extract the temporal dependencies of the dataset. Attention Based CNN model: This model employs an Attention-Based Convolutional Neural Networkin accordance with [13] to extract spatial features from EEG- based images. This image is segmented into a 1 second time frame and each time frame is projected on to a 2D scalp map. In the proposed attention based CNN framework mainly consists of four convolutional layers and three pooling layers, where each convolution was followed by arrays of ReLU activation and attention modules that provide feedback to each feature map and the pooling section (Fig. 3).

The first convolution layer utilized 32 filters of dimension 3×3 possessing stride of 1, and zero-padding to maintain spatial dimensions. Convolutional filtering was the same in all layers with the same size kernel and depth increasing in deeper layers to extract higher-level features. Max Pooling followed each convolution, with a 2×2 window and stride of 1 for each Max Pooling layer to down sample across layers. The feature maps were subsequently flattened, and fed into a fully-connected layer to generate an ultimate feature vector (spatial) for classification.

Attention-based Bi-LSTM model: A Bi-LSTM network can extract temporal features from EEG signals by taking the input sequence in forward, as well as, backward directions simultaneously. Each LSTM unit consists of a memory cell, as well as input, forget, and output gates to modulate the information flow. For a given input sequence X =[x1, x2,..., xT], Bi-LSTM generates an output sequence Y =[y1, y2,..., yT]. , where each output yt is obtained by combining the forward and backward hidden state at time step

Fig. 3 Experimental Setup

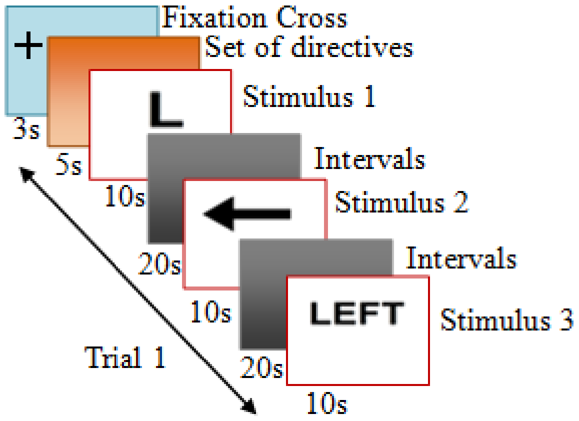

Fig. 4 stimulus presentation and Experimental protocol

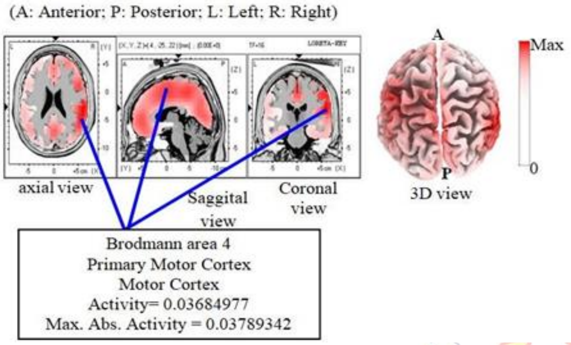

Fig. 5 (a) e-LORETA solutions obtained during Left arm Motor Imagery

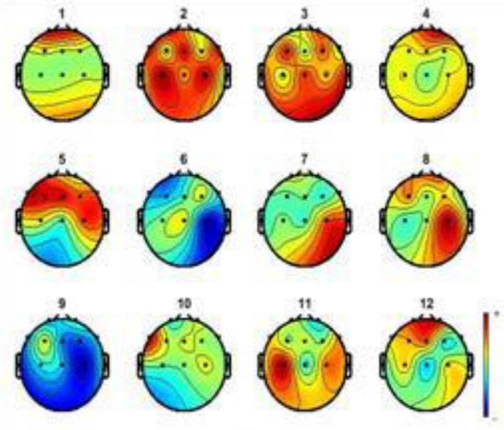

Fig.6. Scalp map for 12 important components during left arm motor imagery using ICA

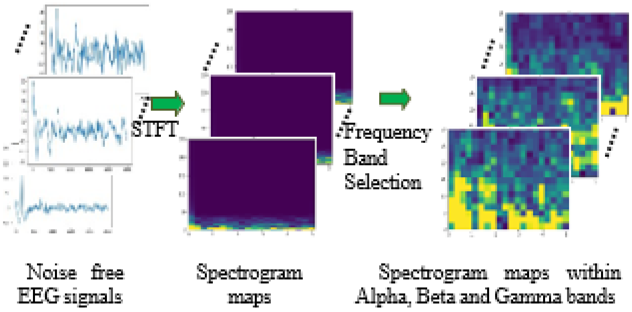

Fig. 7. Spectrogram analysis of three different frequency bands collected from active electrodes

Each LSTM unit applies the sequence *S* by modifying the memory state through three gates on time step *t*.

1. The forget gate decides the information to keep from the

past:

$$ft = \sigma\, (WfsSt + Wfhht \circledcirc 1 + bf\,) \qquad (1)$$

2. The input gate defines how much new information to permit into memory and also compute the candidate state ˆ . *ct*

$$it = \sigma\, (WisSt + Wihht \circledcirc 1 + bi\,)$$

$$\hat{}\; ct = \tanh\, (\, WcsSt \circledcirc Wchsht\text{-}1 + bc \qquad (2)$$

3. Now, The cell state can be updated by mixing the information from memory at time step t−1 and the new information: ˆ) $ct = ft \circledcirc ct \circledcirc 1 \circledcirc it \circledcirc ct)$

4. Finally, the output gate controls the information flow into the next timestep, creating the hidden state:

$$ot = \sigma\, (WosSt + Wohht \circledcirc 1 + bo\,),\ ht \circledcirc ot \circledcirc \tanh(ct\,) \qquad (3)$$

An attention mechanism is implemented on top of the outputs of the Bi-LSTM in order to improve discrimination. The attention mechanism will assign weights αt to the hidden states:

$$\alpha_t = \frac{\exp(h_t)}{\sum_{k=1}^{T} h_k}, \qquad y = \sum_{t=1}^{T} \alpha_t h_t. \qquad (4)$$

Here, *y* is the weighted context vector that summarizes the most informative time steps. The context vector is fed to a dense layer (that aligns with the CNN dimension) to generate the final temporal feature vector. Finally, the spatial features (from CNN) and temporal features (from Bi-LSTM + Attention) are fused together to create a spatio-temporal representation. The contextual representation is then fed to a dense layer with a softmax classifier applied to output class probabilities: Image stylization, also referred to as artistic style transfer, has gained substantial attention in recent years due to its wide-ranging applications in digital art, media production, entertainment, virtual reality, and content creation platforms.

$$\hat{y}_i = \frac{e^{Z_i}}{\sum_{j=1}^{c} e^{Z_j}} \qquad (5)$$

IV. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

This section outlines the experiments and findings for classifying EEG based motor imagery signals into four directional categories left, right, forward, and backward.

A. Experimental protocol and Stimulus Preparation

The experiment has been conducted at the Institute of Engineering and Management (IEM) laboratory, located in Salt Lake, Kolkata. The data acquisition was performed by a 32-channel EEG device manufactured by NUROMAX PVT. LTD, Medicaid Systems as described in Fig. 3. EEG signals were recorded using gold cup electrodes located on the scalp based on the well-known international 10–20 electrode placement scheme [14]. Thirty volunteers (20 female and 10 male), aged between 20 and 45 years, took part in this study. Participants were instructed to sit comfortably, keeping their arms on the armrests, to minimize the effect of movement on EEG artifacts.

The experiment protocol included four motor imagery (MI) tasks corresponding to the direction of target movement. The protocol for each trial had a single sequence: a 5-second preparatory screen (the participant prepares for the task), followed by a 10-second stimulus that would prompt the MI task (the participant thinks about the target movement direction), and a 20-second resting period (where the participant lets the brain return to its baseline as in Fig. 4).

The EEG data was sampled at 512 Hz during task execution. The procedure took place over 10 days and consisted of six sessions per day with five procedures per session.

Table- I Comparative study of the NeuNet model along with traditional models during left hand motor imagery datasets over 30 subjects

Comparative deep learning Models	**Number of Parameters**	**Classification Accuracy (in%)**
CNN [17]	2.12 million	73.88
RNN[18]	0.42 million	76.33
LSTM [19]	1.69 million	74.56
ABCNN [13]	3.00 million	75.98
DCRNN [20]	0.50 million	79.42
Bi-LSTM [21]	3.38 million	81.35
Serial CNN-BiLSTM [22]	5.48 million	85.80
parallel CNN-BiLSTM [22]	5.60 million	85.95
Proposed NeuNet model	**5.50** million	**86.94**

B. Experiment 1: Source Localization by Utilizing the e-LORETA software

The initial studies aimed to localize cortical activation while participants were engaged in motor imagery (MI) tasks. The source localization method used for the eLORETA software, a standard localizing method in three dimensions, allowed for the source localization of the simulated MI tasks. Results indicated significant activation in primary motor cortex (PMA), superior somatosensory cortex (SMA), supplementary motor area (SMA), premotor cortex, and to a lesser extent the prefrontal cortex which is associated with attention and cognitive control (Fig. 5). Overall, this study has demonstrated that MI tasks invoke the sensorimotor network and has established that eLORETA can visualize and map the patterns of cortical activity associated with MI in BCI studies.

C. Experiment 2: Data Pre-processing and Elimination of Artifactual Components

This section describes the pre-processing steps used to remove artifacts and noise contained within the raw EEG signals. The Alpha (8–13 Hz), Beta (12–30 Hz), and gamma (>30 Hz) power increased during the stimulus presentation and was clearly identifiable relative to the stimuli. Therefore, to isolate the relevant activity, we applied a band-pass filter (cut-off frequencies 5–35 Hz). A 10th-order elliptical filter was used because of its superior stopband attenuation and sharp roll-off characteristics [15]. Independent Component Analysis (ICA) was also used across the 16 EEG channels to clean the data from residual artifacts by referring each of the signals to 16 statistically independent components [16]. Thus, muscle movement or eye movement artifacts were easy to identify and remove in independent components. The ICA scalp map for 12 electrodes with respect to left arm motor imagery is shown in Fig. 6

D. Experiment 3: Spectrogram plot from Artifact free EEG signals

This experiment aims to extract spectrogram an image from the noise-free EEG signals to increase the classification performance of a deep learning–based classifier. In order to accomplish this, the Short-Time Fourier Transform (STFT) [12] method is applied to transform the time-domain EEG signals into time-frequency representations. For every trial of the subject, the STFT method generated a 3-D data array, with a size of 129 × 21 × 12, by utilizing a Hamming window of fixed length 256 and 100% overlap on the consecutive frames. Therefore, the feature vectors of the EEG trials were selected within the beta and gamma bands, given these have shown maximum power during motor imageries. This selection allows for the feature space to reduce to a 21 × 21 × 12 dimensional vector that was inputted to classification module to separate four motor imagery directions. The spectrogram analysis of a filtered EEG signal from 16 channels for motor imagery 'Left' of a single participant is shown in Fig. 7

Table- II McNemar's Statistical Test

Relative Algorithms: Proposed attention based CNN-BiLSTM model		
Comparative algorithms	**Z score**	**Acceptance and Rejection of the Null hypothesis**
CNN [17]	11.76	Reject
RNN[18]	8.65	Reject
LSTM [19]	7.45	Reject
ABCNN [13]	6.45	Reject
DCRNN [20]	5.84	Reject
Bi-LSTM [21]	4.33	Reject
Serial CNN-BiLSTM [22]	3.38	Reject
parallel CNN-BiLSTM [22]	3.65	Accept

V. RELATIVE PERFORMANCE ANALYSIS AND STATISTICAL VALIDATION

The proposed classifier architecture combines the advantages of CNN and Bi-LSTM, parameters and dimensions for each of the network modules. In the training phase, the overall learning rate is given as 0.0001 and the dropout value is set to 0.3. The CNN module contains 4 Convolution layers and 4 attention-based max pooling layers with 4 × 4 filter sizes, and 2 × 2 pooling size, with filter counts at 32, 80 and 200 respectively. The Bi-LSTM module contains 300 layers of LSTM networks with a size of 128 for the hidden layer. To evaluate performance against the benchmarks in the literature, results of the Attention based CNNBi-LSTM model were rendered in comparison to common deep learning algorithms, which are outlined in Table I. Each of these algorithms were evaluated on the same dataset and using their respective parameter settings. The results presented validate that NeuNet produced the best classification accuracy (86.94%), outperforming the CNN [17], RNN [18], LSTM [19], ABCNN [13], DCRNN [20], Bi-LSTM [21], serial CNN-BiLSTM models [22], and parallel CNN-BiLSTM models [22]. The Mc-Nemar's [23] statistical validation presented in Table II further affirms the validity of the proposed network. Hypothesis testing was performed using the classifier as a baseline algorithm. The results showed that for all comparisons, we rejected the null hypothesis, and confirmed the validity and robustness of the NeuNet model.T

VI. CONCLUSION

In this paper, the proposed attention-based CNN–BiLSTM framework has demonstrated an effective and robust solution to the motor imagery (MI) classification problem using EEG signals. The approach uses CNNs to extract rich spatial representations of EEG activity, and Bi-LSTM networks to extract temporal dependencies in both the forward and backward direction. An integrated attention mechanism complements the discriminative power of the model by selectively highlighting the most informative time steps within the EEG sequence. The hybrid framework successfully capture the spatiotemporal dynamics of the EEG signals, increasing classification accuracy, compared to conventional deep learning classifiers. The experimental results captured motor-related cortical patterns of multiple MI tasks; sharing the potential to generalize across complex, non-stationary, EEG data. Overall, the research indicates that the attention-based CNN–BiLSTM model has a lot of potential use for real-world brain–computer interface (BCI) systems. This is particularly relevant in the case of assistive technologies and neuro-rehabilitation applications, where accurate and continuous decoding of motor intentions is essential.

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Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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