Classification of Motor Imagery EEG Signals Using Deep Learning

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Abstract **-** Brain-computer interface (BCI) aims to provide a new communication way without the brain's normal output through nerves and muscles. Electroencephalography (EEG) has been widely used for BCI systems because it is a non-invasive approach. In this paper, we proposed a method for extraction and classification of left/right-hand movement using two approaches of deep learning: convolutional neural network (CNN) and combined CNN-LSTM (convolutional neural network - long short-term memory). For the classification of two classes of motor imagery signals, firstly we apply a continuous wavelet transform (CWT) on EEG time series signals to transform signals into 2D images. Next, we train our proposed methods to achieve robust classification from the images. In our work, the proposed methods are validated by the EEG dataset of the BCI competition IIIb. The obtained experimental results show that the proposed CNN-LSTM gives the best results. Our results are promising achieving an interesting mean accuracy of 90.91%.

Keywords - Brain-computer interface (BCI), Electroencephalogram (EEG), Convolutional Neural Network (CNN), Long short-term memory network (LSTM), Motor Imagery (MI), Continuous wavelet transform (CWT).

I. INTRODUCTION

The Brain-Computer Interface (BCI) technology enables people to communicate with external devices using human brain signals [1, 2]. With the advantages of non-invasiveness, portability, low cost, and high temporal resolution, electroencephalogram (EEG) is widely used in BCI systems. The EEG signal is recorded using multiple electrodes placed on the specific scalp areas [3].

There are different control signal types in BCI: visual evoked potentials (VEPs) [3], slow cortical potentials (SCPs) [4], P300 evoked potentials[5], and sensorimotor rhythms [6]. One of the most widely studied EEG-based BCI paradigms is the motor imagery-based BCI. Motor Imagery (MI) is defined as an imagining of kinesthetic movements, and it is well known to modulate sensorimotor rhythm around the motor cortex [7].

Deep learning models (DL) such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory networks (LSTMs) present effective solutions to overcome the problem of low accuracy. These models are already useful in speech recognition, image processing, language modeling, and are applicable for the EEG motor imagery signal classification.

In the literature, several deep learning models have been introduced for the classification of EEG motor imagery. Currently, Xu et al. [8] used continuous wavelet transform (CWT) to transform the EEG signals of three channels (C3, Cz, and C4) into 2D time–frequency maps and used 2D convolution for feature extraction. Y. Shen et al. [9] design a new neural network, which can directly classify the unprocessed EEG data by using a convolutional neural network

(CNN) and long short-term memory (LSTM). Zhao et al. [10] proposed a new 3D EEG data representation by padding the electrode-free channels with zeros and proposing a multibranch 3D CNN for feature extraction and classification. Dai et al. [11] used short-time Fourier transform (STFT) to convert EEG signals into time–frequency images, used 2D CNN for feature extraction, and then fed into deep network VAE (variational autoencoder) for classification.

The goal of this research is to classify MI-EEG signals using DL algorithms with high accuracy.

First, we improved the architectures' performance through simple preprocessing of EEG data. In our case, the raw EEG input data should be transformed into images (scalograms) using CWT. Then, we proposed two methods for classifying MI-EEG signals based on the DL. Finally, we evaluated and compared the performance of the two considered models in terms of classification accuracy.

The remaining paper is structured as follows: Section II presents the dataset used, and briefly explains the methods and relevant theories such as CWT, CNN, and CNN-LSTM. The experimental results and discussion are depicted in Section III. Ultimately, section IV concludes this paper.

II. METHODOLOGY

This section describes the dataset that was considered in this research work. We also provide a full description of the suggested methodology for classification motor imagery using deep learning models.

A) Dataset description

We used the dataset IIIb of BCI Competition 2005, featuring 3 scalp electrode positions. The dataset is provided by the Laboratory of Brain-Computer Interfaces (BCI-Lab), Graz University of Technology. EEG data was collected during a motor imagery task [12].

This dataset contained two classes of EEG data from three subjects (O3, S4, X11). The experiment contains 3 sessions for each subject and each session performs 4 to 9 runs. In the first 2s, nothing happens, at t = 2 s an acoustic stimulus indicates the beginning of the trial, and the trigger was displayed for 1 s. Then at t = 3 s, a visual cue (virtual reality for O3 or basket for S4 and X11) was displayed, and the subject was asked to move a feedback bar in the same direction, by doing movement imagination of left and right hands (Figure. 1).

The EEG was sampled with 125 Hz, it was filtered between 0.5 and 30 Hz with Notch filter on. Details of the dataset are shown in Table 1.

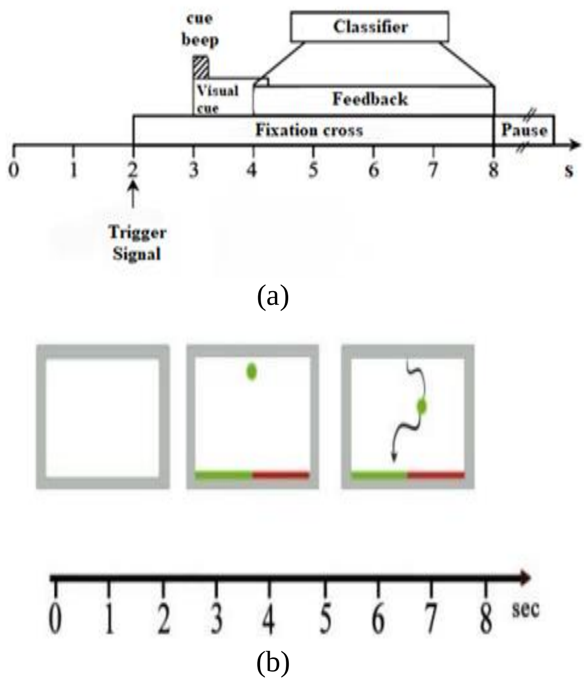


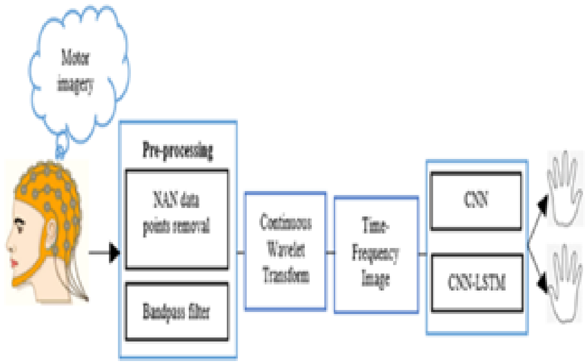
Fig. 1. (a) Paradigm of the virtual reality experiment used for O3, (b) basket paradigm used for S4 and X11.

TABLE 1. DESCRIBING DETAILS OF THE DATASET.

Subject	Feedback	Feedback presentation (s)	Channels	Number of trails
O3	Virtual reality	4–8	C3, C4	640
S4	Basket	4–7	C3, C4	1080
X11	Basket	4–7	C3, C4	1080

B) Proposed work

Our proposed work (Fig. 2) starts with a simple pre-processing of the EEG signals which consists of removing 'NAN' data points and applying a bandpass filter of 8-30 Hz, followed by a step of representation time-frequency using the continuous wavelet transform (CWT). Subsequently, we applied two proposed models: a convolutional neural network in two dimensions (CNN-2D) and the combination of a CNN-2D with a neural network of long short-term memory (LSTM), for modeling and classification of motor imagery EEG signals. CNN allows us to extract spatial features from EEG data, while the LSTM model is often used



to extract temporal features.

Fig. 2. Proposed methodology.

C) Continuous Wavelet Transform (CWT)

Since EEG signals possess non-stationarity and non-linearity, they have the advantage of keeping signal spectrum information along with the time frequency domain. CWT has a mean value of zero and finite wave in time. The parameters of scaling and the shifting in time domain play a critical role in EEG analysis. CWT is defined as the sum over all time of the signal multiplied by scaled, time shifted versions of the wavelet [13, 14]. The formula of continuous wavelet transform (CWT) is:

$$w_{(a,b)}[y(t)] = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} y(t)\varphi^{*}\left(\frac{t-b}{a}\right)dt \qquad (1)$$

Where $\varphi\left(\frac{t-b}{a}\right)$ is a scaled and shifted version of the basis wavelet function $\varphi(t)$, a>0 is the scaling parameter that regulates the spread of the function, and b is the time shift parameter or the instant of time at which the signal needs to be analyzed. Thus, it is effectually identical to bandpass filtering of $y(t)$ at distinct scales.

D) Proposed CNN architecture

CNN is a specific type of neural network that can work well with spatial data. CNNs are particularly useful with images for tasks such as classification or segmentation. Convolutional layers use only certain connections from the previous layer. Specifically, local neurons are connected to the neurons of the next layer. This method causes the layer to gain more of an understanding of the general view of the inputs [15].

The proposed CNN model starts with 4 blocks, each of which contains a convolution layer, the activation function ReLU (Rectified Linear Unit), a maximum grouping layer, then a flattening layer (Flatten), followed by two fully connected layers (FC-5, FC-6) and the SoftMax activation function used to classify the MI tasks (Fig. 3).

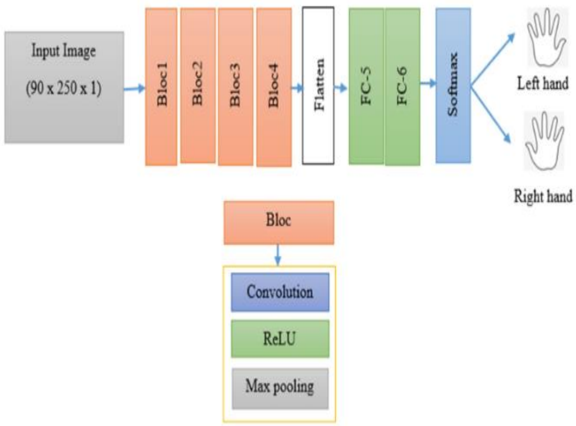


Fig. 3. CNN architecture.

E) Proposed CNN-LSTM architecture

The fusion of both types of neural networks can generate higher performance in task identification owing to the extraction of spatial and temporal features [16, 17]. Thus, the serial structure presented in Fig. 4 is proposed in this study, which is a combination of CNN and LSTM layers. The best-performing structure, according to the optimization results, is composed of four 2D convolutional layers and one LSTM layer. Accordingly, the first four layers each present a 2D convolutional filter component and a ReLu activation function. Additionally, a 2D Max pooling component is fitted with a 2 × 2 dimension of the pooling regions. The following layer corresponds to LSTM, where each layer presents an LSTM component set with 16 hidden units, with the output as a data sequence, a Tanh activation function, and a dropout layer set to a probability value of 0.5. A flatten layer is implemented after the CNN and before LSTM connections. At the end of the structure, two fully connected layers (FC-5, FC-6) and a softmax layer were presented for the classification of the two classes. This network was implemented for all the subjects, as shown in Figure. 4.

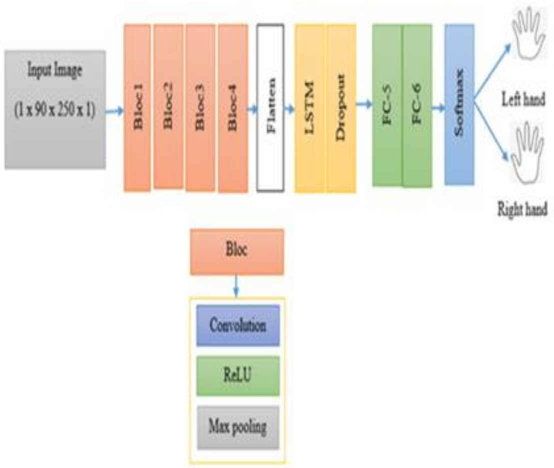


Fig. 4. CNN-LSTM architecture.

In this model, hyper-parameters are configured to 100 training epochs, 16 batch size, and 0.0001 learning rate. For optimizing this model, the Adam optimizer is utilized. A loss function is used depending on the sparse-cross-entropy.

F) Performance metric

The performances of the two proposed models that are based on deep learning are evaluated and compared by the accuracy value (Equation 2) which indicates the percentage of correct predictions of multi-class MI classification. It is defined as follows:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP +TN+FP+FN}} \quad (2)$$

This metric is based on statistical values which are the results of a confusion matrix:

- True Positive (TP) represents an outcome in which a model correctly predicts the positive class.

- True Negative (TN) represents an outcome where a model correctly predicts the negative class.

- False Positive (FP) means a model wrongly predicts the positive class.

- False Negative (FN) presents a model that wrongly predicts the negative class.

III. RESULTATS AND DISCUSSIONS

Experimentally, the proposed models are implemented using Python programming language in a Jupyter Notebook environment. The models are executed on a personal computer with Microsoft Windows 10 operating system, Intel Core i5, 6300 U CPU, 2.4 GHz processor, and 8 GB RAM.

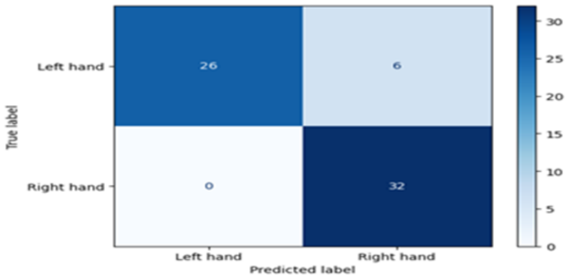
Different approaches to the classification of the motor imagery data have been used to classify the MI signals. Results in terms of accuracy are shown in Tables 2 and 3.

According to Table II, it can be noted the proposed CNN model and the proposed CNN-LSTM reach their maximum values in terms of accuracy, respectively 89.15% and 90.91%. The performance of CNN-LSTM is better in comparison to CNN for classification.

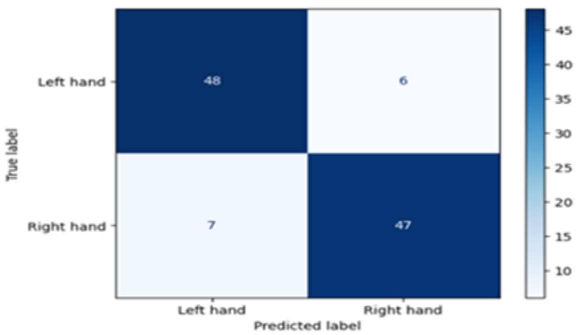
TABLE 2. COMPARISON OF THE ACCURACIES OF THE PROPOSED MODELS .

Models	**O3**	**S4**	**X11**	**Mean (%)**
CNN	90.62	87.96	88.89	89.15
CNN + LSTM	92.19	89.81	90.74	90.91

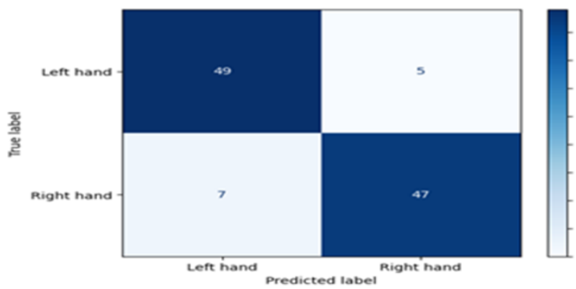
Figures 5 and 6 demonstrates the confusion matrices obtained using different methods. The diagonal elements demonstrate the number of points for which the predicted label is equal to the true label, while off-diagonal elements are those that are mislabeled by the classifier. The higher the diagonal values of the confusion matrix, the better, showing many correct predictions.



O3

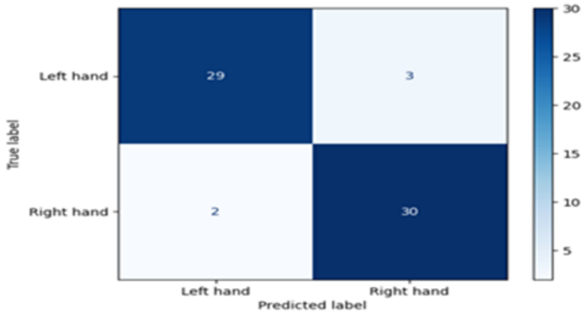


S4

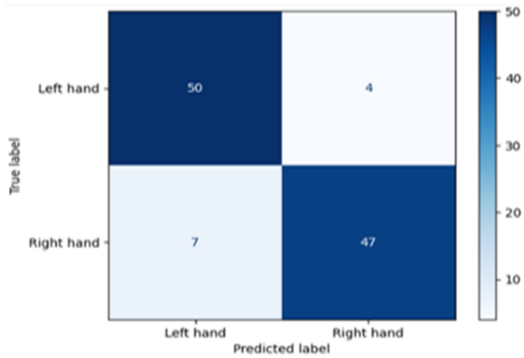


X11

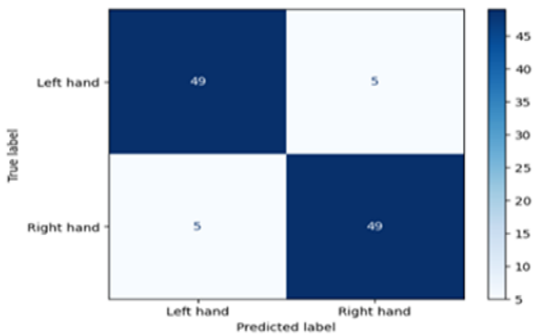
Fig. 5. Confusion matrices obtained by the proposed CNN model



O3



S4



X11

Fig. 6. Confusion matrices obtained by the proposed CNN-LSTM model.

Table 3 compares the classification accuracy of the proposed method with other existing methods used by researchers on the same dataset. Chen et al. reported 78.55% using the linear discriminant analysis (LDA) classifiers based on the AFAPS features are used to classify two Graz datasets used in BCI Competition 2003 and 2005.

Bashashati et al. used multi-layer perceptron (MLP) classifier and wavelet features with 'morl' mother wavelet and reached 80.84%. Fang et al. propose a feature extraction method based on phase space for motor imagery tasks recognition and obtained 84.65% accuracy score. You et al.

proposed a novel classification system for MI-EEG signals is proposed based on flexible analytic wavelet transform (FAWT) and reached 86.66%.

TABLE 3. CLASSIFICATION ACCURACIES COMPARED WITH RECENTLY PRESENTED SAME DATASET METHODS.

Reference	Methods	O3	S4	X11	Mean (%)
Chen et al. [18]	*LDA with AFAPS*	*85.53*	*76.95*	*73.18*	*78.55*
Bashashati et al. [19]	MLP	83.65	82.22	76.67	80.84
Fang et al. [20]	AFAPS + ARPS	90.63	78.52	84.81	84.65
You et al. [21]	FAWT + MDS	93.33	82.41	84.26	86.66
Proposed Models	CNN	90.62	87.96	88.89	89.15
	CNN + LSTM	92.19	89.81	90.74	90.91

The table above shows that, the proposed methods provide better classification accuracy in detecting left and right-hand motor imagery movements than other methods.

IV. CONCLUSION

This paper has presented an implementation of two deep-learning models for MI-EEG signal recognition. Experiments conducted to test the accuracy of the proposed models achieved the testing accuracy for CNN and CNN-LSTM of 89.15% and 90.91%, respectively. The experimental results show that our proposed method based on the proposed CNN-LSTM model, reached the best results compared to CNN model. Moreover, The obtained results show that the proposed methodology is more effective for MI-tasks classification as compared to existing methods. As future works, we will test our proposed models on other databases and extend the detection and classification of other types of MI tasks.

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