Multi-class Motor Imagery EEG Classification using Convolution Neural Network

Amira Echtioui[1,2,a], Wassim Zouch[3,b], Mohamed Ghorbel[1,c], Chokri Mhiri[4,5,d] and Habib Hamam[2,e]

[1]*ATMS Lab, Advanced Technologies for Medicine and Signals, ENIS, Sfax University, Sfax, Tunisia*
[2]*Faculty of Engineering, Moncton University, NB, E1A3E9, Canada*
[3]*King Abdulaziz University (KAU), Jeddah, Saudi Arabia*
[4]*Department of Neurology, Habib Bourguiba University Hospital, Sfax, Tunisia*
[5]*Neuroscience Laboratory "LR-12-SP-19", Faculty of Medicine, Sfax University, Sfax, Tunisia*

Keywords: Electroencephalogram (EEG), BCI, CNN, LSTM.

Abstract: Electroencephalogram (EEG) signals based on Motor Imagery (MI) are a widely used form of input in Brain Computer Interface (BCI). Although there are several ways to classify data, a question remains as to which method to use in EEG signals based on motor imagery. This article presents an attempt to reach the best classification method based on deep learning methods by comparing two models: Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM), on the same basic data set. The BCI Competition IV dataset 2a was used as the base dataset to test the two classification methods. Experimental results show that the proposed CNN model outperforms the LSTM model, with an accuracy value of 74%, and other state-of-the-art methods.

1 INTRODUCTION

BCI is a method of communication between a system and a user that does not depend on the muscles or normal nerve pathways that exit the brain. The process begins with the acquisition of the user's brain activities and is followed by the processing of EEG signals to detect the user's intentions. This signal is then sent to an external device, such as a wheelchair, which is then controlled according to the detected signal. Hence, the identification of motor imagery movement intentions is of great importance in the field of Artificial Intelligence Rehabilitation Medicine. As per the literature, in-depth learning methods have gained enormous success in signal, image, video, speech, and other areas, which perform better than hand-craft methods.

In reference (Tabar et al., 2017), the authors present a hybrid deep learning model that combines the CNN model and Stacked AutoEncoder (SAE). They demonstrate a powerful capability for the classification of IM tasks. Other authors of reference (Ma et al., 2018) developed an LSTM by proposing a temporal and spatial recurrent neural network that outperforms other methods with a gain of 8.25% in classification accuracy.

In reference (Shen et al., 2017), the authors combine RNN with CNN in order to improve the feature representation and classification capabilities of MI-EEG. In reference (Shen et al., 2017), an end-to-end LD approach using CNNs and LSTMs in the long and short term is proposed for the classification of raw EEG data without applying any pre-processing. A model with CNN input for a separate spatial and temporal filtering producing good results despite the architecture is very simple (Schirrmeister et al., 2017). Our objective is to propose a new Deep Learning-based method to enhance the performance

[a] https://orcid.org/0000-0003-2041-1301
[b] https://orcid.org/0000-0003-1047-1968
[c] https://orcid.org/0000-0003-0821-0398
[d] https://orcid.org/0000-0001-7591-6994
[e] https://orcid.org/0000-0002-5320-1012

Echtioui, A., Zouch, W., Ghorbel, M., Mhiri, C. and Hamam, H.
Multi-class Motor Imagery EEG Classification using Convolution Neural Network.
DOI: 10.5220/0010425905910595
In *Proceedings of the 13th International Conference on Agents and Artificial Intelligence (ICAART 2021) - Volume 1*, pages 591-595
ISBN: 978-989-758-484-8

of the motor imagery classification. The main research contributions to this work may be summarized as follows:

- Application of a simple pre-processing of the data: removal of EOG channels and extraction of three second period epochs from the data set in 288 events for the 4 classes;
- Selection of EEG channels;
- We propose two new methods of classifying MIs based on deep learning: modified CNN and modified RNN-LSTM;
- The proposed method based on CNN allows for the classification of MI with an accuracy of 74%.
- The comparative results show that the proposed modified CNN-based method could offer the best performance in achieving the highest accuracy value compared to recent state of the art approaches.

The remainder of this paper is organized as follows. Our proposed method is presented in Section 2. Results and the discussion are detailed in Section 3. Section 4 concludes the paper.

2 METHODOLOGY

In this section, we provide a description of the database used in this work. We also present a detailed description of the methodology proposed to classify MIs based on deep learning methods.

2.1 Data Set Description

In this work, we use multi-class motor imagery EEG data from the BCI Competition IV 2a dataset. This dataset includes nine subjects who performed motor imagery tasks in four classes: left hand, right hand, feet and tongue. The EEG data for each subject consists of 288 trials of the MI task in four classes and each class of tasks was tested 72 times. EEG signals were recorded with 22 EEG channels and 3 EOG channels, sampled at 250 Hz and a bandwidth filtered between 0.5 and 100 Hz. The paradigm of the single MI task is shown in Figure 1.

2.2 Proposed Work

We propose two deep learning-based methods for the classification of motor imagery. Figure 2 displays the block diagram of our proposed technique. Our proposal begins with a pre-processing step where we removed the EOG channels and extracted the epochs of 3 s time period from the dataset into 288 events for all 4 classes. A channel selection step follows. We tested our methodology on 22 electrodes, after which we selected 12 electrodes: Fz, FC3, FC1, FCz, FC2, FC4, C5, C3, C1, Cz, C2, and C4. Finally, we tested two classifiers: modified CNN and modified RNN-LSTM.

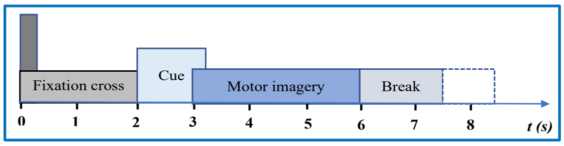

Figure 1: The paradigm time sequence.

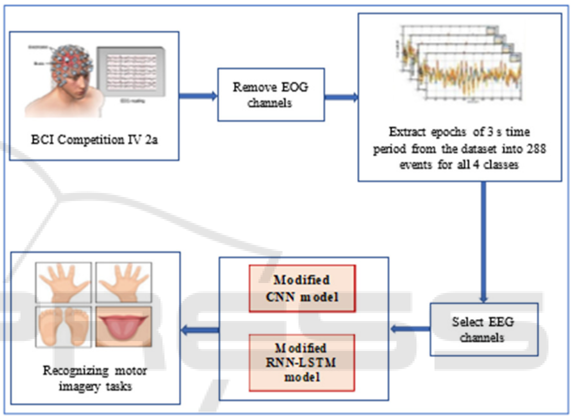

Figure 2: Block diagram of our proposed technique.

2.3 Proposed Modified CNN

Figure 3 shows the proposed modified CNN architecture used to classify the motor imagery tasks. We fine-tuned this model by 250, 500, 750 and 1000 epochs. The batch size is set to 64; the ADAM optimizer is used to optimize the loss function; and the learning rate is 0.001. The activation functions used in this model are ReLu, Elu, Selu, and Tanh.

2.4 Proposed Modified RNN-LSTM

LSTMs are a modified version of RNNs, allowing for easier storage of past data in memory. The problem of the disappearance gradient of RNNs is foreign to LSTM. It is well suited to classify, process and predict time series based on time lags of unknown duration. It drives the model using backpropagation. For more details of RNN and LSTM cells, the reader is referred to reference (Zhang et al., 2019).

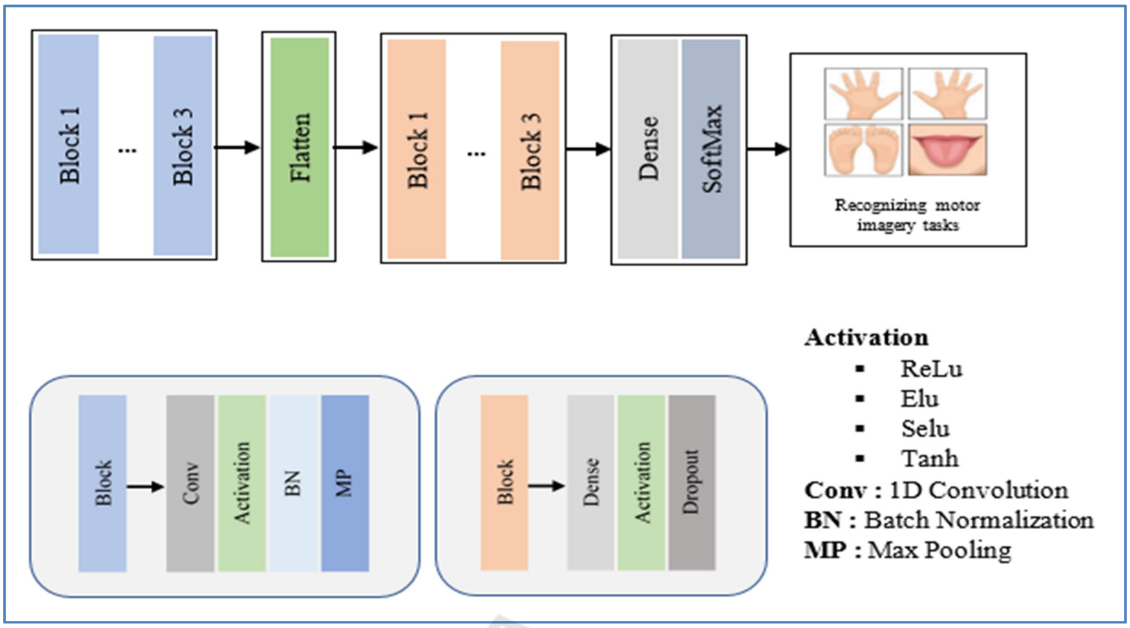

Figure 3: Block diagram of the proposed modified CNN method.

Figure 4 shows the proposed modified RNN-LSTM. We tested this model by 250, 500, 750 and 1000 epochs. The batch size is set to 100, the ADAM optimizer is used to optimize the loss function, and the learning rate is 0.001. The activation functions used in this model are ReLu, Elu, Selu, and Tanh.

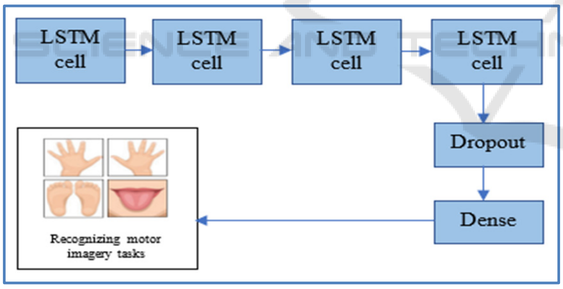

Figure 4: Block diagram of the proposed modified RNN-LSTM method.

3 RESULTS AND DISCUSSION

The performance criterion we used to evaluate the performance of the two models is the accuracy value. It is defined by the rate of correctly classified motor imagery tasks. It is defined by the following equation:

$$Accuracy = TP + TN/(TP + TN + FP + FN) \quad (1)$$

where:

- ***TP (True Positive)*** is the number of motor imagery tasks that are correctly detected;
- ***TN (True Negative)*** is the number of non-motor imagery tasks that are correctly classified as non-motor imagery tasks;
- ***FP (False Positive)*** is the number of motor imagery tasks that are incorrectly determined by a classifier; and
- ***FN (False Negative)*** is the actual number of motor imagery tasks that are incorrectly assigned to other classes.

In tables 1 and 2 and Figure 5, the classification accuracy of each network is calculated for the 22 EEG channels. It can be seen that the modified RNN-LSTM did not produce a superior performance, scoring a 70% accuracy with the Elu activation function (1000 epochs) compared to the modified CNN classifier. The latter produced the greatest accuracy value of our work reaching 74% with the Elu activation function after 750 epochs.

At the same time, the results obtained for the modified CNN and the modified RNN-LSTM-based methods with the selection of 12 channels demonstrated both the same classification precision value, that is 56% after 1000 epochs.

This value is achieved by the modified CNN with the ReLu activation function and by the modified RNN-LSTM with Selu. After comparing these methods, it is found that the modified CNN is the most optimal architecture, of which the classification accuracy far exceeds the accuracy rates of the modified RNN-LSTM.

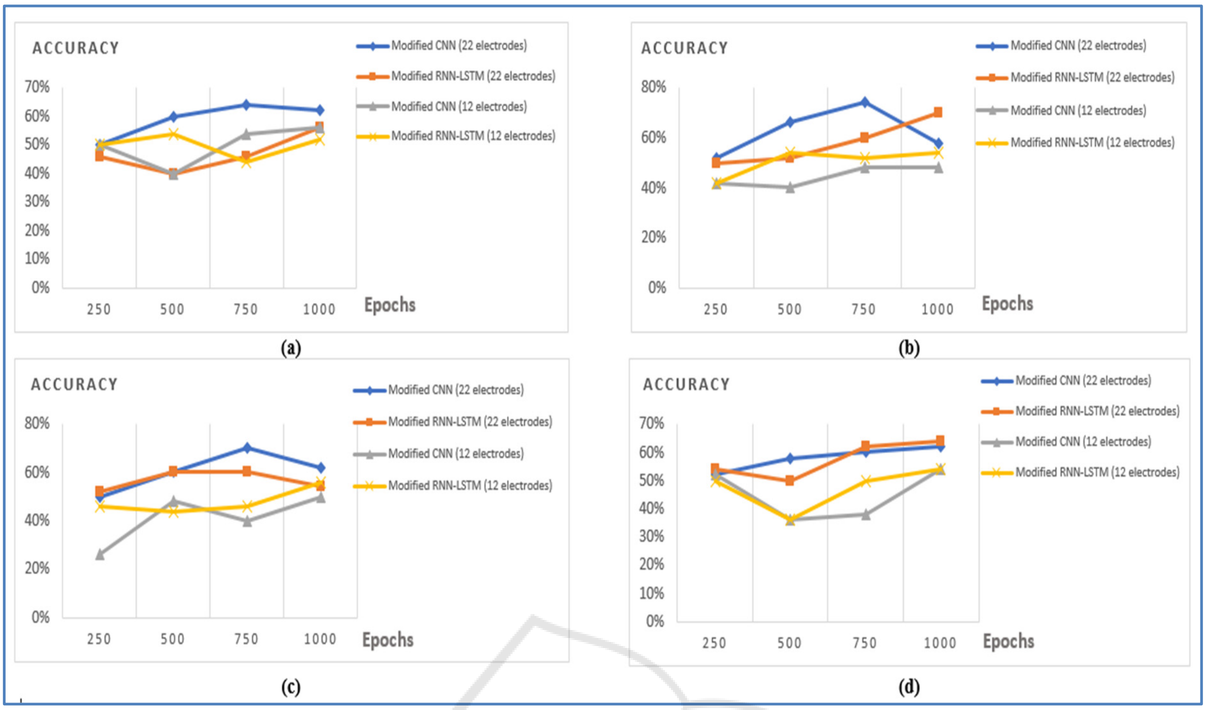

Figure 5: Classification result with: (a) the Relu function, (b) the Elu function, (c) the Selu function, and (d) the Tanh function.

Table 1: Accuracy values obtained by the modified CNN.

Epochs number	Modified CNN (22 electrodes)				Modified CNN (12 electrodes)			
	Relu	**Elu**	**Selu**	**Tanh**	**Relu**	**Elu**	**Selu**	**Tanh**
250	50%	52%	50%	52%	50%	42%	26%	52%
500	60%	66%	60%	58%	40%	40%	48%	36%
750	64%	**74%**	70%	60%	54%	48%	40%	38%
1000	62%	58%	62%	62%	56%	48%	50%	54%

Table 2: Accuracy values obtained by the modified RNN-LSTM.

Epochs number	Modified RNN -LSTM (22 electrodes)				Modified RNN -LSTM (12 electrodes)			
	Relu	**Elu**	**Selu**	**Tanh**	**Relu**	**Elu**	**Selu**	**Tanh**
250	46%	50%	52%	54%	50%	42%	46%	50%
500	40%	52%	60%	50%	54%	54%	44%	36%
750	46%	60%	60%	62%	44%	52%	46%	50%
1000	56%	70%	54%	64%	52%	54%	56%	54%

Table 3: Summary of the research on classification of motor imagery tasks.

Reference	**Method**	**Accuracy**
(Fadel et al., 2020)	DCNN-LSTM	70.64%
(Zhuozheng et al., 2019)	EEGnet	67.76%
Proposed model	Modified CNN model	74.00%

We consider in Table 3 a summary of the results on the classification of motor imagery tasks of EEG signals and a comparison with our proposed method. The summary proves that the proposed modified CNN model outperforms the other models in terms of accuracy.

In reference (Fadel et al., 2020), the authors proposed a classification method in which the EEG signals are transformed into images using deep learning. They used a Physionet dataset, which includes 109 subjects, and MI EEG signals for three frequency bands were transformed into three-channel images using Azimuthal equidistant projection and the Clough- Tocher algorithm for interpolation. These 2D images represent the input data of the DCNN which is used to extract frequency and spatial characteristics. A LSTM is applied to extract temporal features and classify the results into 5 different classes (4 MIs tasks and a pause). They obtained an average accuracy of 70.64%.

In reference (Zhuozheng et al., 2019), the authors adopted a shallow EEGnet network, and used one-dimensional convolution for EEG classification in the time domain. They extract only the one-dimensional characteristics of the EEG signals. They obtained an accuracy value of 67.76%.

Our proposed method provides the highest accuracy value despite its simplicity and the minimal pre-processing of the data. Moreover, we notice that reducing the number of electrodes does not always give better results.

4 CONCLUSIONS

We applied two methods based on deep learning for the classification of MI tasks using EEG signals. We demonstrated that the modified CNN is more efficient than the modified RNN-LSTM model in terms of classification. We compared our results with recent results obtained using other classification methods and showed that our proposed method gives a higher accuracy than other methods. We believe that our approach can be used to increase the efficiency of BCI based on motor imagery.

ACKNOWLEDGMENT

This work was carried out under the MOBIDOC scheme, funded by the European Union (EU) through the EMORI program and managed by the National Agency for the Promotion of Scientific Research (ANPR).

REFERENCES

Fadel, W., Kollod, C., Wahdow, M., Ibrahim, Y., & Ulbert, I., 2020. Multi-Class Classification of Motor Imagery EEG Signals Using Image-Based Deep Recurrent Convolutional Neural Network. *8th International Winter Conference on Brain-Computer Interface (BCI)*.

Ma, X., Qiu, S., Du, C., et al., 2018. Improving EEG-Based Motor Imagery Classification via Spatial and Temporal Recurrent Neural Networks. *40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE*.

Schirrmeister, R. T., Springenberg, J. T., Fiederer, L. D. J., Glasstetter, M., Eggensperger, K., Tangermann, M., Hutter, F., Burgard, W., and Ball, T., 2017. Deep learning with convolutional neural networks for EEG decoding and visualization, *Human Brain Mapping*, vol. 38, no. 11, pp. 5391–5420.

Shen, Y., Lu, H., and Jia, J., 2017. Classification of motor imagery EEG signals with deep learning models, *in International Conference on Intelligent Science and Big Data Engineering (Lanzhou: Springer)*, pp. 181–190.

Shen, Y. Lu, H. and Jia, J., 2017. Classification of motor imagery EEG signals with deep learning models*, in Intelligence Science and Big Data Engineering: 7th International Conference, IScIDE 2017. Springer International Publishing*, pp. 181–190.

Tabar, Y R., Halici U., 2017. A novel deep learning approach for classification of EEG motor imagery signals. *Journal of Neural Engineering*.

Zhang, G., Davoodnia, V., Sepas-Moghaddam, A., Zhang, Y., & Etemad, A., 2019. Classification of Hand Movements from EEG using a Deep Attention-based LSTM Network. *IEEE Sensors Journal*.

Zhuozheng, W., Zhuo, M., Xiuwen, D., Yingjie, D., Wei, L. 2019. Research on the Key Technologies of Motor Imagery EEG Signal Based on Deep Learning*, Journal of Autonomous Intelligence*.