Automated Motor Imagery Detection Through EEG Analysis and Deep Learning Models for Brain-Computer Interface Applications

Yang Li[1], Bocheng Liu[2]*, Yujia Tian[3]
School of Physical Education, Harbin University, Harbin 150086, Heilongjiang, China[1]
School of Software, Nanchang University, Nanchang 330047, Jiangxi, China[2, 3]

***Abstract*—The classification of motor imagery holds significant importance within brain-computer interface (BCI) research as it allows for the identification of a person's intention, such as controlling a prosthesis. Motor imagery involves the brain's dynamic activities, commonly captured using electroencephalography (EEG) to record nonstationary time series with low signal-to-noise ratios. While various methods exist for extracting features from EEG signals, the application of deep learning techniques to enhance the representation of EEG features for improved motor imagery classification performance has been relatively unexplored. This research introduces a new deep learning approach based on two-dimensional CNNs with different architectures. Specifically, time-frequency domain representations of EEGs obtained by the wavelet transform method with different mother wavelets (Mexicanhat, Cmor, and Cgaus). The BCI competition IV-2a dataset held in 2008 was utilized for testing the proposed deep learning approaches. Several experiments were conducted and the results showed that the proposed method achieved better performance than some state-of-the-art methods. The findings of this study showed that the architecture of CNN and specifically the number of convolution layers in this deep learning network has a significant effect on the classification performance of motor imagery brain data. In addition, the mother wavelet in the wavelet transform is very important in the classification performance of motor imagery EEG data.**

Keywords*—Brain-computer interface (BCI); Electroencephalogram (EEG); motor imagery; deep learning; classification

I. Introduction

Brain-computer interfaces (BCIs), with the aim of helping people with muscle disabilities who have cognitive potential, analyze brain signals and convert them into control commands without direct use of peripheral nerves and muscles [1]. The general function of BCI is to first receive brain signals as input, extract useful features from the signal, classify them, and finally convert them into a control command [2]. Among the types of BCIs, motion imagery systems have been increasingly used in various fields. In this type of BCI system, when the subject moves a part of his body (such as the right or left hand) or imagines movement, the brain frequency profile changes in the μ and β frequency range [3]. These phenomena show event-related synchronization (ERS) and event-related desynchronization (ERD), based on which brain signals affected by motor imagery can be classified [4]. In general, studies on the classification stage of these systems are conducted using classical machine learning methods and modern deep learning approaches [5]. Classical machine learning methods have two relatively independent parts feature extraction and classification [6, 7]. One of the major challenges in classical machine learning methods is the extraction of appropriate features and inefficiency in dealing with nonlinear data [8, 9]. In order to solve these problems, the use of deep learning methods for data classification gradually increased [10], and in recent years, with the increasing progress of hardware, the use of these methods for various applications, including data classification in motor imagery problem, has grown significantly [11]. In contrast to conventional approaches, deep learning has the capability to autonomously acquire sophisticated high-level features and underlying traits through intricate architectures directly from unprocessed motor imagery EEG signals. This eliminates the need for time-consuming preprocessing and feature extraction. Among the scrutinized studies, CNN emerged as the most commonly utilized technique for classifying motor imagery in the EEG signals [12]. The common practice in employing raw signal data with deep learning techniques, with or without minimal preprocessing, was apparent. However, recent comprehensive reviews suggested that despite the advancements made by deep learning in enhancing the interpretation of motor imagery EEG signals, the practical deployment of motor imagery based BCI systems in real-world scenarios continues to face impediments in terms of technical complexities and user-friendliness [3, 5, 13]. Therefore, there is still no comprehensive solution for the problem at hand, and our effort in this work is to find an optimal solution for one of the technical challenges of EEG classification of motion imagery. In fact, two research objectives are pursued in this work. First, providing a deep two-dimensional CNN model with minimum complexity and processing time that can be added to BCI systems in the future. Second, finding the best wavelet function to extract 2D images from the EEG signal to integrate with 2D CNN for the problem at hand. The solutions presented in this paper can help future studies to achieve an optimal motor imagery EEG based BCI system. The rest of this paper is arranged as follows: Section II reviews the related works in the literature of this field. Section III presents the proposed methods including the used database, time-frequency analysis, and deep learning models. Experimental results are presented in Section IV. Section V provides a discussion of the results and proposed methods. Finally, a brief conclusion is provided in Section VI.

*Corresponding Author.

II. Related Works

Due to the complexity involved in recording and the limited availability of signals, the utilization of deep-learning-based classification methods in BCI applications remains infrequent. Li and Zhu et al. [14] utilized the optimal wavelet packet transform (OWPT) for constructing feature vectors from motor imagery EEG data. These feature vectors were employed in training a long short-term memory (LSTM) model based on a recurrent neural network (RNN). The performance of this algorithm was found to be excellent on dataset III of the BCI Competition 2003. However, the structure of the algorithm appeared to be excessively intricate. On the other hand, Liu et al. [15] introduced a novel CNN architecture for the classification of P300 signals. The algorithm achieved remarkable results on the BCI competition P300 datasets. Despite the impressive performance of these deep learning methods in classification tasks, it is worth noting that these networks typically exhibit complexity and involve a large number of parameters. In the publication referenced as [16], Bashivan et al. employed power spectrum densities derived from three different frequency ranges of EEG signals. They proceeded to generate images for each frequency range by interpolating topological features that accurately represented the brain's surfaces. Their approach involved utilizing the VGG (visual geometry group) model, blending 1D convolutions with LSTM layers. The research outcomes demonstrated that the ConvNet and LSTM/1D-Conv architectures outperformed alternative models. In another study referenced as [17], the authors also adopted a CNN architecture, but with a distinct approach. They first employed the convolutional layer and then utilized the encoder portion of the AutoEncoder. Furthermore, they incorporated the power spectral densities of fast Fourier transforms as a feature set in their experimentation.

Ju and Guan [18] introduced a new geometric deep model called Tensor-CSPNet to specify the spatial covariance matrices of EEGs on symmetric positive definite manifolds. This framework was applied to motor imagery EEG datasets and achieved current state-of-the-art performance in cross-validation and holdout techniques. Zhang et al. [19] investigated five different adaptive transfer learning-based schemes to adapt a CNN-based EEG-BCI system to decode hand motor imagery. They obtained an average accuracy of 84% for the two-class motor imagery problem. Hwang et al. [20] proposed an LSTM-based classification method based on overlapping sliding windows to acquire time-varying EEG data. They demonstrated that their proposed method outperforms existing algorithms for EEG classification of four motor imagery classes, and also exhibits robustness to inter-trial and inter-session motor imagery data variability. Liu et al. [21] proposed a new end-to-end compact multi-branch 1D convolutional neural network for EEG-based motor imagery classification. They reported average classification accuracies of 83.92% and 87.19% on two public datasets. Wang et al. [22] proposed a 2D hybrid CNN-LSTM algorithm for EEG classification in motor imagery tasks. They converted the EEGs into time series segments and then calculated the connectivity features between EEG electrodes in every segment via 2D CNN and finally fed the feature vectors to the LSTM network for training. Li et al. [23] proposed a new dual-attention-based adversarial network for motor imagery classification. Their framework uses multi-subject knowledge to enhance the classification performance of single-subject motor imagery tasks through intelligently utilizing a new adversarial learning algorithm and two unshared attention blocks. Dang et al. [24] proposed a modular CNN, Flashlight-Net model, for Motor Imagery EEG Classification. Due to the multi-frequency nature of the brain, they combined the three frequency bands and built an ensemble model of Flashlight-Net using transfer learning.

One of the main problems of all previously presented models is their structural and computational complexity, which severely limits their real-time application in BCI systems. In this article, we intend to design a CNN model to create an optimal and stable network for motor. In imagery classification the following, we will introduce the data, proposed methods, and findings, and finally discuss and conclude the findings.

III. Methods

A. Dataset

In this article, the BCI competition IV-2a dataset held in 2008 [25] was utilized for testing the proposed deep learning approaches. This data includes EEG signals with 22 signal recording electrodes, which are placed on people's heads with 10-20 standard, from nine normal subjects. The signals are sampled with a frequency of 250 Hz and filtered with a 0.5 to 100 Hz band-pass filter. The signal recording protocol is based on cues and includes four movement perception tasks (right hand, left hand, legs, and tongue movement perception). In this data, the signal recording for each subject was done in two sessions, each recording session consists of six tasks, and in each task, 48 trials (12 trials per movement perception class) and a total of 288 trials were recorded for each subject. At the beginning of each test (t=0), a + sign appears on the screen, after two seconds (t=2s) with a short sound warning, the + sign turns into an arrow and goes to one of the up, down, left, and right directions. Then, with a short rest, the subject performs the next test. Fig. 1 shows the timing scheme of a trial.

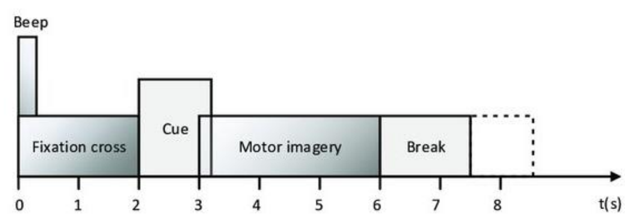


Fig. 1. Timing scheme of a trial in BCI Competition IV-2a dataset.

B. Proposed Framework

The purpose of this article is to classify brain signals based on motor imagery using two-dimensional CNNs. For this four-class classification problem, the proposed method includes the implementation of two-dimensional CNNs with the input of time-frequency data obtained by the wavelet transform method with different mother wavelets and comparing the performance of this network in order to classify the data. In general, the proposed method is shown in the block diagram of Fig. 2. This framework included data preprocessing, time-frequency transformation using different mother wavelets, classification through two-dimensional CNNs, and performance evaluation. In the following, the details of each of these steps are described.

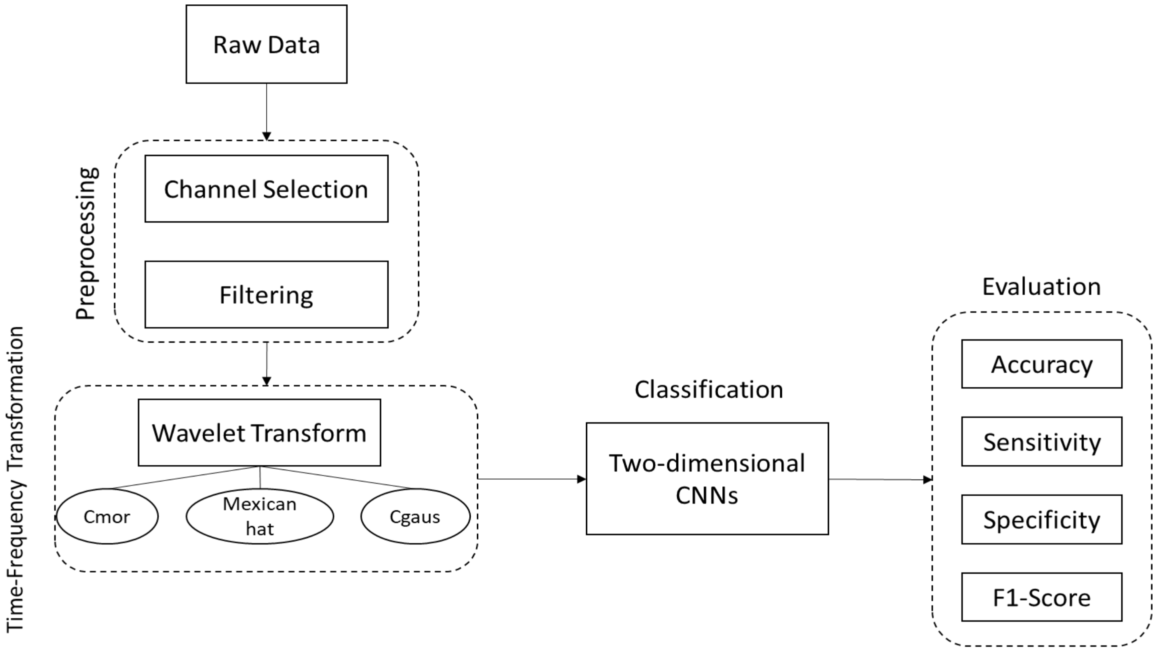


Fig. 2. Block diagram of the proposed framework for motor imagery EEG classification.

C. Data Preprocessing

At first, in order to select suitable and effective channels, for each subject, all 22 signal recording channels were checked and channels were selected that have more information related to movement perception signals according to the anatomical structure of the brain. The selected channels for each subject were C4, C3, and Cz channels, which are located in the sensorimotor area of the brain. Fig. 3 shows the location of these electrodes on the scalp. Also, considering that motor imagery often occurs in the μ and β frequency range, an 8-30 Hz Butterworth band-pass filter (5th order) was applied to the EEG.

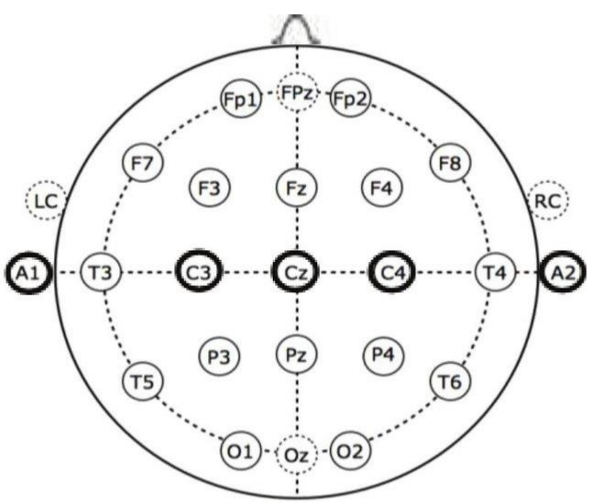


Fig. 3. Location of C3, C4, and Cz EEG channels used for motor imagery classification.

D. Time-Frequency Analysis

CNNs necessitate the use of images as input, which means that the one-dimensional EEG should be transformed into two-dimensional images. To achieve this, the continuous wavelet transform (CWT) is a commonly used time-frequency technique that decomposes a time series into its frequency and time (1/scale) components. The CWT was developed to address the resolution issue of the Short-Time Fourier Transform (STFT) and produces high-resolution scalogram outputs. Using the Fourier transform alone is not a suitable approach considering that it is not sensitive to parameters such as time or frequency resolutions which are very important in the analysis of motor imagery. Therefore, it is recommended to use methods such as the wavelet transform, which has good accuracy both in terms of time and frequency [26]. CWT allows for time-frequency analysis of EEG signals, which is important in EEG processing as it provides information about how signal characteristics change over time. CWT offers variable resolution in both time and frequency domains [27]. This means that it can provide high time resolution when analyzing high-frequency components and high frequency resolution when analyzing low-frequency components. CWT exhibits shift-invariance property, which means that small shifts in the signal do not significantly impact the wavelet coefficients. This property can be beneficial when analyzing EEG signals which may have slight time delays due to various factors [28]. This technique involves convolving a time series with a series of functions generated through a continuous function known as the mother wavelet. The CWT for a specified time series, s(t), can be computed using Eq. (3):

$$CWT_{(a.b)}[s(t)] = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{+\infty} s(t)\Phi^{*}\left(\frac{t-b}{a}\right)dt \quad (1)$$

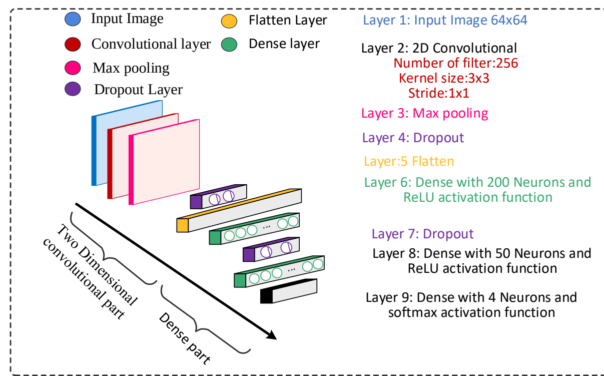
where, a, b, and Φ denote the scale factor, the translational variable, and the basic wavelet function, respectively. In this article, CWT with three different mother wavelets Cmor, Mexicanhat, and Cgaus was used to convert the time domain to the time-frequency domain, so that among these three mother wavelets, the most powerful one is selected for data processing in motor image classification.

E. Deep Learning Models

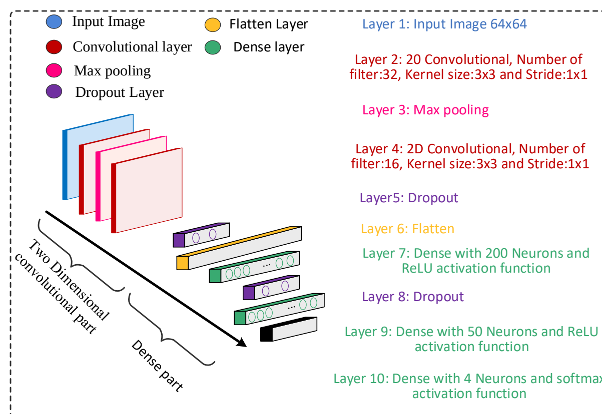
Previous studies have shown that CNN is an effective and superior method compared to other methods in motor imagery data classification, and it has received much attention [19, 29, 30]. CNNs are able to capture local patterns in data irrespective of their location, making them suitable for EEG signals which are often affected by noise or small variations in electrode placement. CNNs can automatically learn hierarchical representations of the input data, starting from simple features (like edges or curves) to more complex features. This ability is beneficial for capturing the intricate patterns present in EEG signals. CNNs are known for their ability to learn meaningful representations from relatively small datasets. This is advantageous in EEG classification where collecting large amounts of labeled data can be challenging and expensive [31]. CNN architectures can be easily scaled to handle different EEG datasets with varying sizes and complexities. By adjusting the depth and width of the network, CNNs can adapt to different EEG classification tasks efficiently [32]. Therefore, in this paper, the classification performance of two-dimensional CNNs for images obtained from wavelet transform with three mother wavelets, Mexicanhat, Cmor, and Cgaus, was investigated. For this purpose, two different 2D CNN architectures are proposed with the aim of classifying motor imagery-based data. In the first architecture, the network includes a convolution layer consisting of 256 kernels with dimensions of 3×3 and step 1. The next layers include the Max pooling layer and a Dropout layer to prevent overfitting. In order to prepare the data for classification, a flattened layer and then two fully connected layers are used. In the second architecture, the network consists of two convolution layers. In the first layer, 32 kernels with dimensions of 3×3 and step 1 are used, and in the second layer, 16 kernels with dimensions of 3×3 and step 1 are used. Among the convolution layers, a Max pooling layer and a Dropout layer are used, a flattened layer is used for data preparation, and two fully connected layers with 200 and 50 neurons, respectively, are used for classification. The architecture of these two networks is shown in Fig. 4. The proposed models incorporate various adjustments for the count of filter, size of stride, and other parameters. Hidden layer dimensions were decreased from the input size to four, representing count of groups in suggested network. It is important to mention that the hyperparameter values were carefully fine-tuned based on a thorough examination of relevant literature and extensive testing. Only optimal parameters were selected for suggested networks. Several optimization functions were explored, like Adam, Stochastic Gradient Descend (SGD), CyclicLR, StepLR, and ReduceLR. Nonetheless, due to superior performance in practical applications, the SGD algorithm was chosen as optimizer with a learning rate of 0.0002 and a batch size of 64. Additionally, training process was controlled by cross-entropy loss function. Best parameters for suggested network are summarized in Table I.

TABLE I. OBTAINED OPTIMAL PARAMETERS FOR SUGGESTED DEEP MODELS

Parameter	Tested domain	Selected Value
Number of convolutional layers	1, 2, 3, 4, 5	Model 1: 1 Model 2: 2
Count of filters in the convolutional layers	16, 32, 64, 128, 256	Model 1: 256 Model 2: 32, 16
Filter size in the convolutional layers	3, 16, 32, 64	Model 1: 3 Model 2: 3
Activation function	ReLU, LReLU	ReLU
Cost function	Cross-entropy, MSE	Cross-entropy
Optimizer	Adam, Adamax, RMSProp, SGD	SGD
Dropout level	0.1, 0.2, 0.3, 0.4, 0.5	0.5
Batch size	4, 8, 16, 32, 64	64
Learning rate	0.001, 0.0001, 0.0002, 0.0003	0.0002



(A)



(B)

Fig. 4. Two-dimensional convolutional neural network architectures are proposed to classify the brain data of motor imagery: (A) the first proposed architecture, and (B) the second proposed architecture.

IV. RESULTS

Fig. 5 shows an example of EEG signals related to selected channels for motor imagery classes 1 and 4. Moreover, Fig. 6 shows an example of time-frequency maps resulting from wavelet transform in selected EEG channels using mother wavelets Cmor, Mexicanhat, and Cgaus. As shown, there was an obvious difference in the time-frequency maps obtained from different wavelet mothers, which may affect the classification performance of deep learning models.

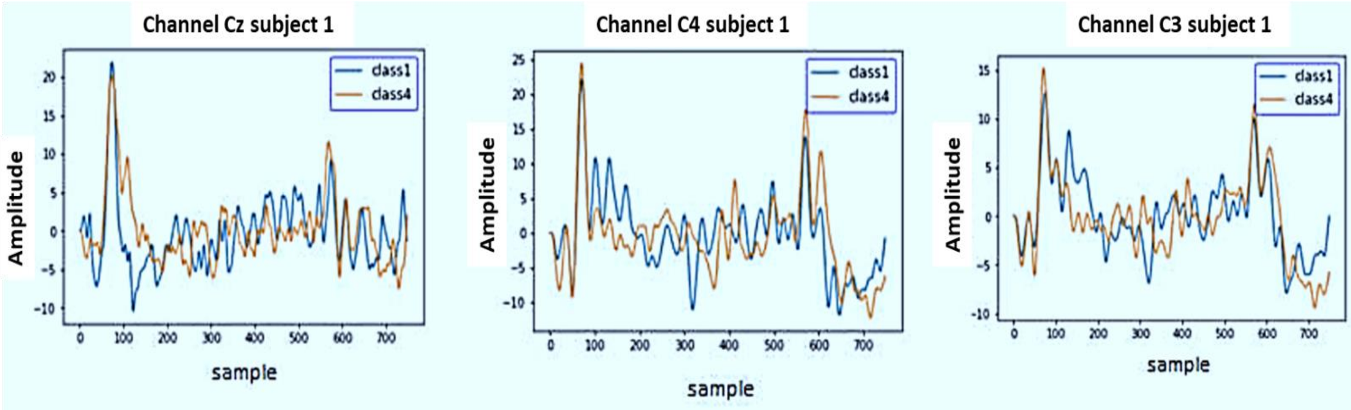


Fig. 5. An example of EEG signals related to selected channels for motor imagery classes 1 and 4.

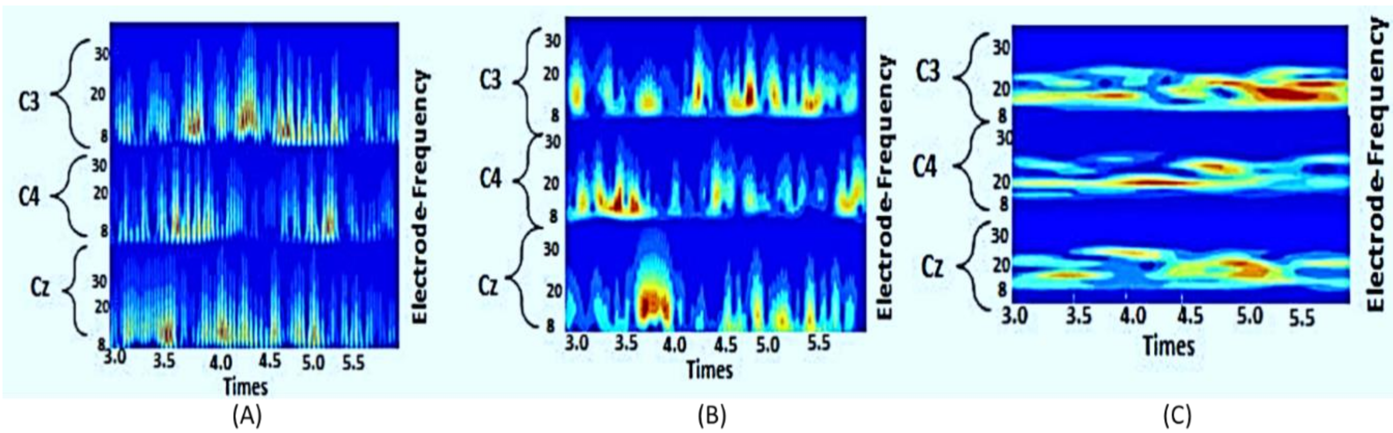


Fig. 6. An example of time-frequency maps resulting from wavelet transform in selected EEG channels using mother wavelets is (A) Cmor, (B) Mexicanhat, and (C) Cgaus.

One of the important steps after designing and building a model is to evaluate that model. In classification problems, this evaluation is based on four elements: true positive, true negative, false positive, and false negative. In this study, four criteria of accuracy, precision, recall, and F1-score were used for an individual-based classification strategy. The results of the implementation of the first and second architectures of two-dimensional CNN with three mother wavelets Mexicanhat, Cmor, and Cgaus in nine subjects and with the evaluation criteria of accuracy, precision, recall, and F1score are shown in Tables II and III. The results showed that the second architecture with two convolution layers performs better than the first architecture. The best classification result was obtained through the second CNN architecture and mother wavelet Cgaus with 92.54% accuracy, 94.11% precision, 95.06% recall, and 93.37% F1-score.

TABLE II. THE RESULTS OBTAINED THE FIRST CNN ARCHITECTURE USING DIFFERENT MOTHER WAVELETS FOR MOTOR IMAGERY CLASSIFICATION

Subjects	Accuracy (%)			Precision (%)			Recall (%)			F1-score (%)		
	Cmor	***Mexicanhat***	***Cgaus***	***Cmor***	***Mexicanhat***	***Cgaus***	***Cmor***	***Mexicanhat***	***Cgaus***	***Cmor***	***Mexicanhat***	***Cgaus***
Subject 1	93.22	85.97	93.94	94.32	87.15	94.58	95.57	88.00	95.47	94.42	86.10	94.21
Subject 2	87.32	74.4	89.02	89.23	75.30	90.44	90.42	77.41	92.26	88.13	79.37	89.86
Subject 3	67.27	59.18	66.91	70.07	60.67	67.92	70.98	61.33	68.96	69.48	60.02	67.32
Subject 4	91.52	78.42	91.97	92.87	79.97	93.21	93.41	81.08	93.88	92.20	79.11	92.68
Subject 5	95.8	88.98	96.13	96.65	90.02	97.64	98.01	90.96	98.39	96.68	89.46	97.03
Subject 6	89.43	88.07	89.94	90.31	89.90	91.66	92.27	90.22	93.17	90.10	88.93	90.35
Subject 7	95.46	80.07	95.78	96.68	81.84	97.45	97.33	82.21	98.00	96.24	80.99	96.41
Subject 8	83.47	80.04	84.01	84.63	81.69	85.45	84.99	82.02	87.41	83.97	80.88	84.99
Subject 9	96.87	94.67	96.89	97.30	95.34	98.37	97.94	98.95	98.91	97.04	95.42	97.22
Average	88.92	81.08	89.39	90.23	82.48	90.75	91.22	83.25	91.83	89.81	81.82	90.02

TABLE III. THE RESULTS OBTAINED THE SECOND CNN ARCHITECTURE USING DIFFERENT MOTHER WAVELETS FOR MOTOR IMAGERY CLASSIFICATION

Subjects	Accuracy (%)			Precision (%)			Recall (%)			F1-score (%)		
	Cmor	*Mexicanhat*	*Cgaus*	*Cmor*	*Mexicanhat*	*Cgaus*	*Cmor*	*Mexicanhat*	*Cgaus*	*Cmor*	*Mexicanhat*	*Cgaus*
Subject 1	94.23	93.43	97.57	95.98	94.99	90.68	96.85	96.14	99.06	95.35	94.19	98.03
Subject 2	89.72	86.35	88.90	91.24	88.67	90.11	92.47	89.40	91.37	90.55	87.64	89.33
Subject 3	70.57	68.57	74.53	71.35	70.06	76.90	72.41	72.59	78.37	70.99	69.44	75.49
Subject 4	90.06	89.85	95.42	91.96	91.46	96.88	92.68	93.29	97.68	91.00	90.67	96.04
Subject 5	95.70	93.86	96.15	97.77	95.44	98.03	98.51	96.90	99.00	96.44	94.79	97.35
Subject 6	96.52	96.05	96.17	97.94	97.85	98.30	98.00	98.30	99.01	97.20	97.10	97.77
Subject 7	97.36	96.79	95.66	98.81	97.91	97.07	98.98	98.57	97.99	97.90	97.47	96.57
Subject 8	91.21	90.57	89.77	91.93	91.88	91.48	93.66	93.45	93.37	92.11	91.42	90.38
Subject 9	98.72	97.48	98.87	99.02	98.95	99.49	99.57	99.02	99.98	98.97	98.33	99.34
Average	91.57	90.33	92.54	92.90	91.92	94.11	93.92	93.08	95.06	92.28	91.25	93.37

V. DISCUSSION

EEG motor imagery classification plays a crucial role in various fields, especially in the domain of BCI technology. By utilizing EEG data, this classification technique allows the interpretation and extraction of meaningful information from brain signals associated with motor imagery tasks. The significance of EEG motor imagery classification lies in its potential to enable individuals with motor disabilities to regain control of their environment and interact with external devices using their thoughts alone. It opens up new possibilities for applications such as neuro-rehabilitation, prosthetics control, and assistive technologies. Moreover, EEG motor imagery classification contributes to advancing our understanding of brain functioning and provides a non-invasive means to study and analyze neural processes related to motor planning and execution. Through continued research and development, EEG motor imagery classification holds promise for enhancing the quality of life for individuals with motor impairments. In this article, with the aim of designing a classification system of motor imagery data based on deep learning methods, two different CNN architectures were investigated. For this purpose, after reviewing the studies conducted in this field, the proposed systems were introduced and implemented, and the details of these systems were examined. The proposed model with the aim of classifying motion perception data includes the blocks of channel selection, filtering, data transformation to the time-frequency domain, classification, and evaluation of the proposed model. Among the examined wavelet transforms, the images created with the Cgaus mother wavelet had the best classification performance in both CNN architectures. In addition, among the proposed CNN architectures, the second architecture with two layers of convolution showed the best performance, which was confirmed by various evaluation criteria including accuracy, precision, recall, and F1score.

In Table IV, the results obtained from the proposed method are compared with the previous classical machine learning and deep learning approaches. All these publications have used the same dataset as our study and therefore it is possible to directly compare the previous and current proposed methods. As shown, the proposed method performs very well compared to the previous classical machine learning and deep learning methods. However, it should be noted that deep learning methods increase the computational costs, and to reduce the computational load and maintain the classification quality, it is necessary to conduct more studies on the network structure, such as the number of kernels, the use of one-dimensional kernels instead of two-dimensional kernels, and the number of layers used. Also, considering the variety of existing mother wavelets, more studies on the wavelet transform with other mother wavelets are suggested.

TABLE IV. COMPARING THE RESULTS OF THE PROPOSED DEEP LEARNING METHOD WITH THE PREVIOUS STATE-OF-THE-ART WORKS FOR THE CLASSIFICATION OF THE BCI COMPETITION IV-2A DATASET

Reference	Algorithm	Classifier	Reported accuracy (%)
[33]	SFBCSP	SVM	92
[34]	CTDA	SVM	81.85
[35]	Variance	FN	78
[36]	Variance	TSLDA	70.20
[37]	CSP	LDA	89.23
[38]	WT	2D CNN	87.60
[39]	CWT	VGG-16	68.33
[40]	WT	2D CNN	85.59
[41]	CSP+WT	2D CNN	72.25
[42]	WT	2D CNN	89.36
Current work	WT	2D CNN	92.54

VI. CONCLUSION

In this work, two simple CNN models with different and yet simple structures were proposed and investigated for motor imagery EEG classification. For this purpose, time-frequency representation of EEG signal was used as input of deep models. Both research goals of this work were achieved: (1) increasing the accuracy of motor imagery EEG classification compared to previous existing techniques using simple deep learning architectures; and (2) investigating the effect of the mother wavelet on the time-frequency representation of the EEG signal as an input to deep learning networks and determining the best mother wavelet to achieve appropriate results. In summary, the findings of this study showed that the architecture of CNN and specifically the number of convolution layers in this deep learning network has a significant effect on the classification performance of motor imagery brain data. In addition, the findings of this study showed that the mother wavelet in the wavelet transform is very important in the classification performance of motor imagery EEG data. Considering that many EEG studies use time-frequency maps obtained from wavelet transform as input to deep learning models, the results of this study can be very useful and important for this type of study.

Although the proposed method achieved better performance than some state-of-the-art methods, this study faced limitations that should be further investigated in future research. One of the limitations of this study was the selection and analysis of only three EEG channels based on anatomical information related to motor perception, while other channels may also contain useful information that can help improve the performance of the proposed system. Therefore, it is recommended that future studies use automatic channel selection and optimization methods to utilize the maximum relevant information available in brain signals. In this study, only three well-known mother wavelets were compared and investigated, while new hybrid mother wavelets have been introduced in recent years that can improve the performance of the proposed framework. Therefore, further studies on wavelet transform with other mother wavelets are suggested. In addition, there are new time-frequency analysis methods that may perform better than traditional wavelet transforms, such as empirical Fourier decomposition and empirical wavelet transform. It is strongly recommended that future studies explore the integration of these new methods with the proposed deep models.

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