Multi-channel of electroencephalogram signal in multivariable brain-computer interface

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ABSTRACT

Brain-computer interface (BCI) usually uses Electroencephalogram (EEG) signals as an intermediate device to drive external devices directly from the brain. The development of BCI capabilities is carried out by involving multivariable EEG signals as movement commands. EEG signals are recorded using multi-channel, enriching information if it uses the suitable method and architecture. This research proposed a two-dimensional convolutional neural networks (CNN) method to recognize multi-channel EEG signals. The vertical dimension is the channel, while the horizontal is the signal sequence. Hence, the signal is connected with the information time series of the same channel and between channels simultaneously. BCI was arranged with multivariable signals, specifically motor imagery and emotion. Both variables have different characteristics, and the information is from different channels. Therefore, it needs multiple CNNs to recognize the two variables in the EEG signal. The experiment showed that the accuracy of multiple 2D-CNN increased to 94.62% compared to 85.44% of single 2D CNN. Multiple 2D-CNN gave accuracy from 82.04% to 94.62% more than multiple 1D-CNN. 2D-CNN makes the channel extraction perfect into vectors to maintain the signal sequence. Signal extraction is essential, so the used Wavelet filter upgraded accuracy from 73.75% to 94.62%.

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1. INTRODUCTION

Brain-computer interface (BCI) is a computer and machine interaction technology that allows moving external devices through brain commands without involving gestures, muscles, and voice. BCI is a way to communicate human brain and computers directly. Technology development can help someone with a physical disability drive an external device. BCI has gained more application challenges [1], so it has given attention and recognition in medical rehabilitation to help post-stroke patients [2], wheelchairs [3], and neuromuscular defects [4]. BCI was developed as a prosthetic hand in the rehabilitation process for stroke survivors [5]. This technology is also used for practicality or entertainment, such as games [6], movement imaging of games [7], real-time robots [8], education [9], military, and other applications [10]. BCI works by receiving brain command input, which intermediate appliances capture to drive external devices. An electroencephalogram (EEG) signal is often used as intermediate translate brain command to control an external device. BCI actions often use EEG signals due to their high time resolution, relative convenience, low cost, and effectiveness compared to other methods [11].

Commands executed by BCI involve more variables captured from the EEG signal. BCI can be driven by conscious command through imagined and is called motor imagery (MI). Previous research used motor imagery to identify hand movements, imagination [12], control mouse [13], and external devices such as wheelchairs [14]. Brain motor imagery includes, among others, such as arithmetic, imagination, movement, and singing [15]. There are steady-state visually evoked potentials (SSVEP), and P300 evoked potentials. MI is actively so can control the equipment as they imagine. While SSVEP and P300, although the high-speed transmission speed, need additional equipment, which is less convenient in implementing BCI [16].

Emotion identification was a coupling connection [17], so it can drive BCI [18]. There are exogenous and endogenous BCI variables. Exogenous machines need to use external conditions for brain stimulation to produce a specific response, such as steady-state visual evoking or SSVEP [19]. Emotion includes an exogenous part of the neuropsychological in BCI development [20]. Endogenous is such as motor imagery with imagining something as a command. Emotion and physiological states are related to feelings [21] and are essential for daily interactions and physical motor activities [22]. Alpha and Beta waves represented neutral and happy emotions in the 8-30Hz range [23]. In several previous studies, MI induced emotion [24]. BCI with motor imagery outperformed emotions stimulating motor imagery [24]. However, involving emotions can enrich BCI control. Moreover, electrical activity in the brain also occurs unconsciously, such as emotions, to induce motor imagery [24], so combining the two also becomes a brain command [25]. Others used multivariable commands such as motor imagery and focus variables [26].

The EEG signal used for BCI control can be single-channel or multi-channel. Usually, a single channel is arranged with a simple stimulation such as a blink [27] or two relaxing actions or not [6]. This research used BCI of EEG multi-channels. At the same time, it used multivariable EEG signals, specifically motor imagery and emotion. Both variables come from EEG signals of different channels and different patterns and characteristics. Separating into different networks will save memory and increase performance. Furthermore, emotions that induce motor imagery become a class that engages both. Therefore, it needs multiple networks.

Convolutional neural networks (CNNs) and recurrent neural networks (RNN) are often used to identify commands through EEG signals in BCI. CNN is good at extracting features automatically and addressing various tasks end-to-end. RNN is good at learning sequence data like EEG signals to hand movement imagination [12]. Previous studies used the RNN in identifying motor imagery induced by emotion [28], motor imagery and focus used RNN gave an accuracy of 77.88% [26]. Each variable that is processed by each network comes from multi-channels. Therefore, choosing a suitable model to simultaneously maintain signal connectivity between channels and time sequence signals in the same channel. The 2D CNN architecture allows signal connectivity between channels and across time simultaneously. The result of feature extraction using 2D CNN becomes the input of the time sequence using RNN. Therefore, it is called Spatio-temporal. A previous study processed each channel of the Parallel Sequence-Channel Projection 2D-CNN EEG signal with an accuracy of 95.96% and 96.24% [29]. Selection of the correct number of channels increased the average accuracy by about 20% [30]. Therefore, the EEG signal from multiple channels can be treated as spatial in the channel direction and time sequence as temporal, thus giving an emotion recognition accuracy of 74.4% and 71.4%, respectively [30].

Motor Imagery is characterized by wave activity in the Mu frequency band due to the desynchronization of rhythm patterns [31], usually from the sensory-motor cortex or Fp5 and Fp6 channels (from the dataset used). Several studies have shown that Beta bands also have the potential for this event [32]. It has also been shown that frequency bands are often subject-specific and can vary slightly for the subject [33]. Mu and Beta waves in the 8-30Hz band [13]. While neutral and joyful emotions are in Alpha and Beta with 8-30 Hz [25].

A frequency filter is needed to direct the EEG signal pattern of each variable. Filters focused on small data in classification to improve performance [34]. Some studies used fast fourier transform (FFT) [35]. In comparison, other studies use Wavelet [31]. Wavelets have advantages in decomposition for non-stationary data such as EEG signals. The Wavelet filters signals in the Alpha, Mu, and Beta frequency bands. Previous research used to identify motor imagery and emotion variables, with an accuracy of 90% [25].

This research used EEG signals through motor imagery and emotion variables as the BCI control. The proposed method used multiple networks that separate each variable with different characteristics and channels. EEG signals are filtered using Wavelets and are extracted spatial-temporal using 2D-CNN. In addition to saving memory in recognizing patterns, separating the network, and following a combination of the two variables. Previous studies yielded higher accuracy multi CNN than single networks [36].

2. RESEARCH METHOD

BCI commands can pass EEG signal information with one or more variables. Motor imagery is when the brain imagines specific movements, often used in BCI actions. During the motor imagery, Mu and Beta waves are desynchronized so that the two waves at a frequency of 8-30Hz represent the motor imagery pattern. Emotions often occur in an unconscious state, so they inevitably induce BCI. Therefore, motor imagery and emotion as BCI action variables make up eight classes, as shown in Figure 1. For this purpose, the EEG signal is filtered using Wavelet first. The two variables are processed with separate networks so that the action combines the two classes. The details of each process are described next. It is why the architecture is called multivariable BCI of multi-channel EEG. Using two-dimensional CNN or 2D CNN facilitates the processing of multi-channel EEG signals.

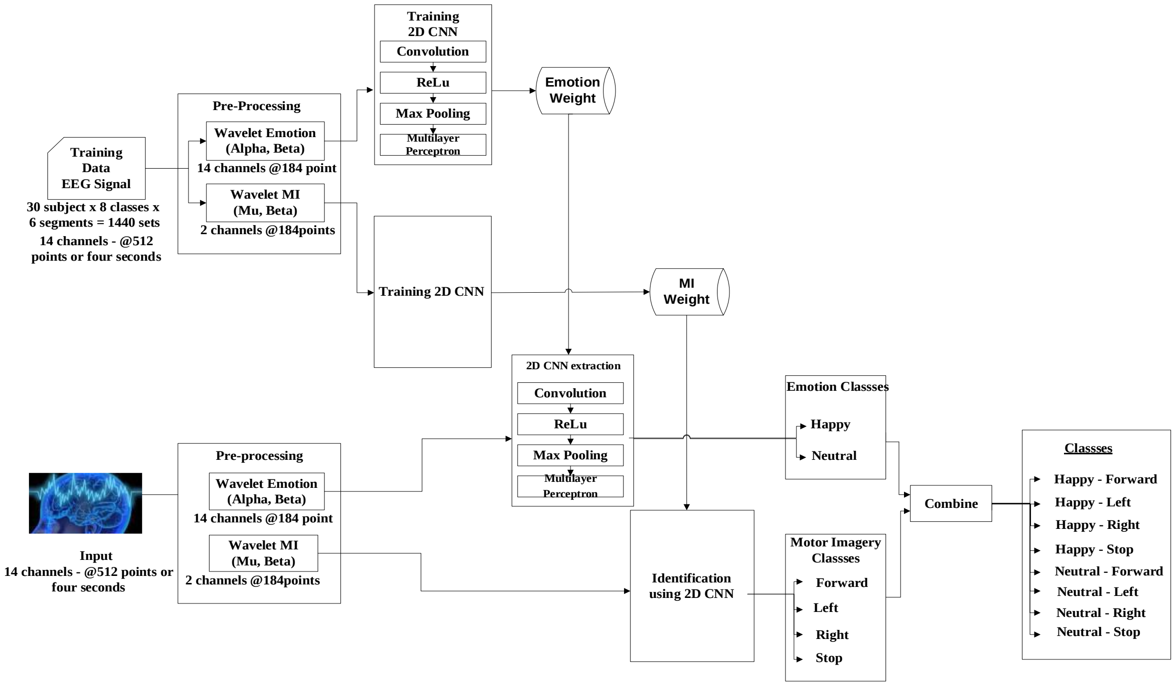


Figure 1. Multi-channel EEG signal in multivariable BCI

The computational model like Figure 1. EEG signals as training data were taken from 30 volunteers from eight classes, with emotions: happy and neutral, and motor imagery: forward, left, right, and stop. BCI command every four seconds, so each data during this time for training and testing.

2.1. EEG datasets

Training and validation data were obtained from recording EEG signals for four seconds from 30 people aged 18-25 years in healthy, cooperative settings so that not reviewed variables could be ignored. EEG instrument used Emotiv Epoch from 14 channels with 128Hz sampling frequency [25]. There are two classes of emotion as stimulation: neutral and happy. Four motor imagery classes are forward, stop, right, and left. Data were taken by 30 subjects x 8 classes x 6 segments or 1440 sets-the instruction is shown in Figure 2.

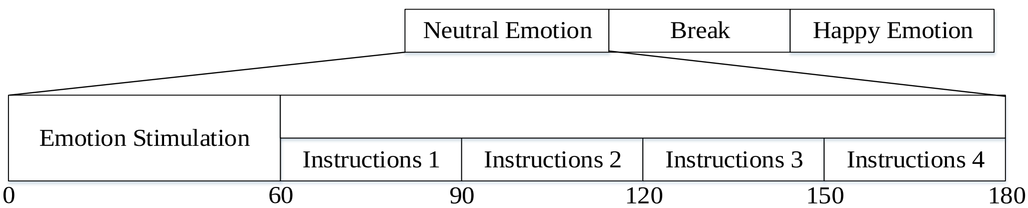


Figure 2. BCI dataset with instruction

2.2. Wavelet filter

The digital wavelet transform allows signals to be represented in the time domain and eliminates unwanted frequency bands. A wavelet is a convolution signal with a function defined in (1). The Wavelet transforms the signal by decomposition and reconstruction. Decomposition filters a specific frequency signal by dividing it into two parts, the low-frequency approximation (2) and the detail representing the high frequency (3), as shown in Figure 3. The reconstruction combines the signal back into its time domain [37].

$$\psi_{\sigma,\tau}(n) = \frac{1}{\sqrt{|\sigma|}}\psi\left(\frac{n-\tau}{\sigma}\right) \quad (1)$$

$$y_{low}(k) = \sum n\, x(n).\, g(n-k) \quad (2)$$

$$y_{high}(k) = \sum n\, x(n).\, h(n-k) \quad (3)$$

Where g(n) is the coefficient of approximation, h(n) is the details coefficient, x(n) is the original EEG signal, k is the value of shifting, and n is the sequence. In Wavelet, several kernels exist, i.e., Symlet, Daubechies, and Haar. Previous studies used Daubechies (Db4) to be suitable for asymmetric signals [38]. The decomposition is shown in Figure 3.

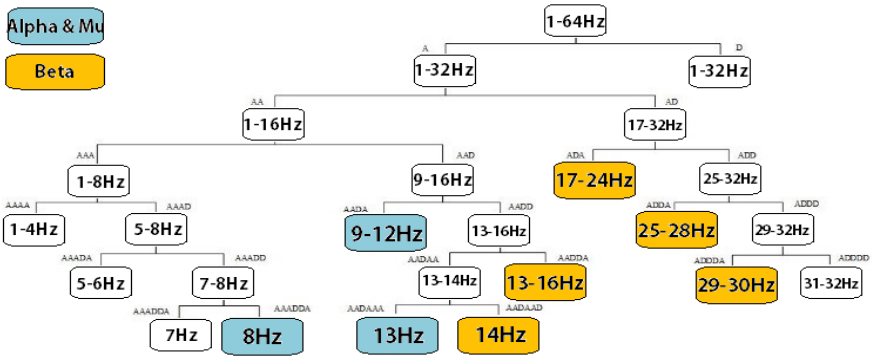
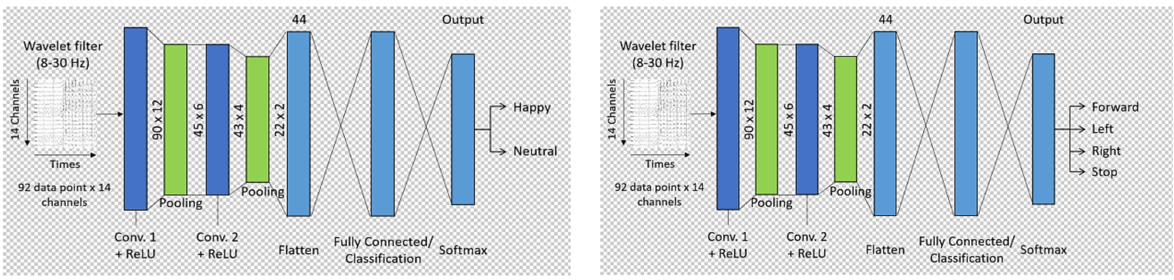


Figure 3. The wavelet of EEG signal 128 sampling frequency and filter 8-30 Hz

2.3. Multiple CNN: Motor imagery and emotion networks

CNNs can work with one, two, and three-dimensional inputs. Although spatial or two-dimensional CNN is widespread, previous studies have converted the EEG signal into time-frequency before using CNN [39]. CNN has two layers, namely feature extraction and classification layer. The feature extraction is convolution, rectifier activation function, and pooling layers, while the fully connected layer manages the classification task [40]. The use of CNN also requires the adjustment of parameters, which determine performance by reducing or minimizing complexity [40]. The use of convolution and activation functions resembles the non-linearity of network computing [39]. Rectified linear unit (ReLU) is often used. Then Max Pooling makes the network coarser without losing the pattern to control overfitting [41]. The results of the extraction process can be seen in Figure 4. There are two networks, particularly CNN architecture for emotion in Figure 4(a) and Motor Imagery architecture in Figure 4(b). So, the 2D-CNN architecture reduces the 512 points of the Wavelet results to 92 points.



(a) (b)

Figure 4. Feature extraction and identification model using 2D CNN from, (a) emotion and (b) motor imagery

In the classification layer, the fully connected neurons. The architecture that is often used is multi-layer perceptron (MLP). Other studies use the support vector machine [42]. The often-used algorithm is backpropagation, which works for weights during training [25]. Accuracy is calculated as the number of correctly identified data. In addition, loss is the difference between the target and the computational output using the cross-entropy function to optimize the parameter [43], with (4).

$$\text{Loss} = -\sum_{i}^{C} t_i \, log(y_i) \tag{4}$$

Where, C is the number of class labels, t_i is the target value, and y_i is the actual output.

3. RESULTS AND DISCUSSION

Experiments in this study were carried out in several parts, mainly the effect of Wavelet filter, using multiple networks, and spatial-temporal networks with 2D-CNN. There are 1440 data sets for the development and validation model. Each subject was given instructions according to the imaginary movement and was stimulated by that specific induced emotion. The dataset was divided into 80% or 1152 for model development or training and 20% or 288 for validation data. The weight correction technique in learning also affects the performance of the model, so it needs to be tested with variations of adaptive moment estimation (Adam), adaptive learning estimation (AdaDelta), and stochastic gradient descent (SGD).

The overall performance of EEG signal identification for multiple BCI variables using multiple 2D-CNN is shown in Table 1. That result used validation data with accuracy and Loss value as performed. Based on the hypothesis and literature review, four parts are tested in the experiment. First, the effect of multiple networks with two EEG signal variables (emotion-induced motor imagery) was compared with single networks. The second experiment is the effect of CNN configuration with spatial-temporal involvement compared with one-dimensional CNN. Third, it is necessary to examine the effect of Wavelet as an EEG signal filter on performance using multiple 2D-CNN. Meanwhile, it is also necessary to experiment with weight correction techniques, viz Adam, SGD, and AdaDelta.

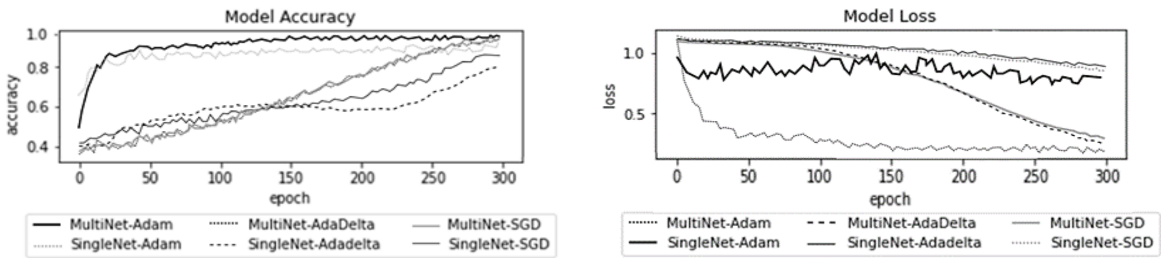
Table 1. The performance of multiple CNN of multivariable

Pre-Processing (Wavelet)	Optimizing Technique	Accuracy (%) 2D CNN Single Networks	Accuracy (%) 2D CNN Multiple Networks	Accuracy (%) 1D CNN Multiple Networks	Loss 2D CNN Single Networks	Loss 2D CNN Multiple Networks	Loss 1D CNN Multiple Networks
With	Adam	85.44	94.62	82.04	0.848	0.110	1.356
	AdaDelta	83.76	92.37	80.88	0.905	0.167	1.269
	SGD	80.11	90.89	81.98	0.877	0.205	1.290
Without	Adam	73.75	74.04	69.25	1.208	1.120	1.356
	AdaDelta	77.88	75.95	70.12	1.110	0.998	1.269
	SGD	76.98	76.12	71.63	1.427	1.105	1.290

In Table 1, the Wavelet filter reduced significant signal components from 512 to 92 points without losing important information. It is seen that Wavelet extraction is the most important, thus giving an increase in accuracy of 28%. It confirms that this process makes it easier for the system to study the EEG signal pattern, which has eight classes of both variables. Meanwhile, using a two-dimensional CNN also affects mapping signals in spatial-temporal. The 2D CNN method provided the flexibility of a connected system between channels and sequences simultaneously. It increased the accuracy by 15.33%. The use of multiple networks also significantly increased accuracy from 85.44 % to 94.62% or 10.74%. The Adam weight correction technique provided the best accuracy. The other methods, specially AdaDelta and SGD, are relatively few. The differences in the three factors are shown in Figures 5-7 of accuracy and Loss value.

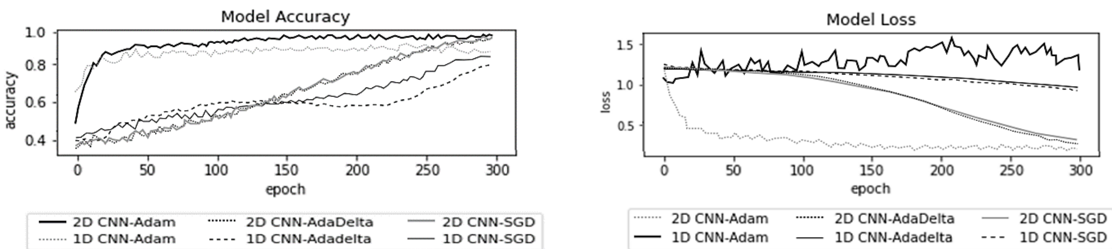
The result showed that using multiple networks increased accuracy and provided stability and faster convergence, as shown in Figure 5. Figure 5(a) shows accuracy in 300 epochs, and Figure 5(b) shows the Loss value. Each network learns to recognize patterns in the same characteristics, either in the contained wave or from a different channel. The three weight correction techniques provide performance that is not much different at a steady state. However, the Adam model has the capability of directional weight correction to improve accuracy, and a decrease in loss value can occur quickly. Compared with the other two models, they tend to be slow due to corrections with random parameters.

While testing the CNN configuration, the accuracy increased higher in 2D-CNN than in 1D-CNN, as in Figure 6. Figure 6(a) shows accuracy in 300 epochs, and Figure 6(b) shows the Loss value-likewise, the decrease in Loss values from all weight correction models. However, Adam steadily improved their performance at the steady-state and stability stages. When the experiment with CNN configuration, both use multiple networks in order to be able to test the most significant effect, whether from multiple versus single or using spatial-temporal CNN, it can be seen that the second method provided an increase in accuracy, which is 15.33%, which can also be seen in Table 1.



(a) (b)

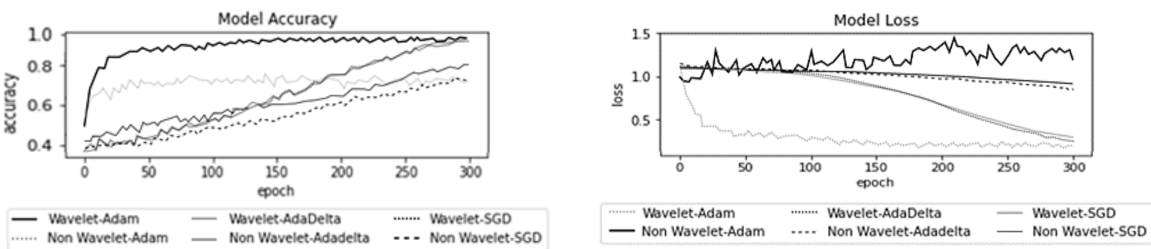
Figure 5. Effect of multi networks compare single networks from the performance of, (a) Accuracy and (b) Loss



(a) (b)

Figure 6. Effect of spatial-temporal using 2D CNN compare 1D CNN from the performance of, (a) Accuracy and (b) Loss

Moreover, the details in Table 1 and Figure 7 illustrate that the role of the Wavelet filter is the most important in identifying EEG signals, and the use of BCI is no exception. Figure 7(a) shows accuracy in 300 epochs, and Figure 7(b) shows the Loss value. The performance is much improved with the Wavelet filter, even though multiple 2D CNNs are used. Performance is determined primarily by selecting the right features in machine learning. It is also seen that Adam remains consistent in performance with any configuration.



(a) (b)

Figure 7. Effect of Wavelet Filter in BCI with multiple 2D CNN from the performance of, (a) accuracy and (b) loss

The following experiment compares 2D-CNN with recurrent neural networks (RNN) between multiple and single networks, as shown in Table 2. The other configurations are set the same. It was found that 2D CNN has a better performance of accuracy and loss value for both multiple and single networks. Interestingly, the performance degradation of single toward multiple networks is more extreme when using

RNN, from 90.57% to 71.56%. While using 2D CNN gave decreasing from 92.37 (multiple) to 83.76% (single) only. Likewise, the use of wavelets from both methods was tested. Moreover, when multiple networks of RNN were used, AdaDelta gave a low accuracy of 60.05%. This phenomenon shows that 2D CNN is more robust than RNN, providing higher performance for signal unfiltered, and single networks are lower than RNN.

Table 2. The performance of 2D CNN toward RNN

Wavelet	Optimizing Technique	Accuracy (%)				Loss			
		Multiple Networks		Single Networks		Multiple Networks		Single Networks	
		2D CNN	RNN	2D CNN	RNN	2D CNN	RNN	2D CNN	RNN
	Adam	94.62	90.57	85.44	71.56	0.110	0.369	0.848	2.012
With	AdaDelta	92.37	60.05	83.76	-	0.167	0.742	0.905	-
	SGD	90.89	81.39	80.11	-	0.205	0.177	0.877	-
Without	Adam	73.75	68.73	74.04	-	1.120	1.322	1.356	-

The BCI configuration of multivariable motor imagery and emotion with multiple 2D CNNs was compared with previous studies for the same data, as in Table 3 for the Adam model. It can be seen that with a deeper convolution, namely the VGG16 architecture, the study using single networks and 1D CNN only provided 87% accuracy with a learning time of up to five minutes. In comparison, multiple 1D CNN networks tested in this study provided an accuracy of only 85.44%, while multiple networks with 2D CNN provided an accuracy of 94.62%. VGG 16 has 13 convolution layers and three Pooling. Of course, it provides deeper learning, so it is reasonable to give high accuracy, but it takes much longer. In this study, it is necessary to VGG16 considering that the CNN input is 3,456 points for each data set due to all variables and all channels being combined. While this study requires only two convolution layers and Pooling provides a much shorter training time, its accuracy is 85.44% for 1D CNN and 94.62% for 2D CNN. However, deep architectures like VGG 16 were not tested.

Table 3. Comparison with previous works

Methods	Accuracy (%)			Learning time (minutes)		
		Architecture		Architecture	Architecture	Architecture
	2 Layers	8 Layers	VGG16	2 Layers	8 Layers	VGG16
Single Networks-1D [25]	-	84.73	87.09	-	4	4.7
Multiple Networks-1D (proposed methods)	82.04	-	-	0.009	-	-
Multiple Networks RNN [28]	90.57			1.450		
Multiple Networks-2D (proposed methods)	94.62	-	-	0.001	-	-

4. CONCLUSION

Using emotion variables from EEG signals that induce motor imagery in the brain-computer interface provides future development opportunities. The development of parallel computing, such as multiple networks, provides a significant performance increase of 15.39%. Meanwhile, the amount of information from many channels from EEG signals needs to be represented in the proper architecture. Therefore, multiple 2D CNN in BCI provides an accuracy of 94.62%, or 10.74 greater than 1D CNN. Meanwhile, another critical factor is the use of filters for signal extraction. Wavelet is the right choice so that it provides an increase in accuracy of up to 28.29%. The chosen architecture and configuration can be applied to other BCI applications or EEG signals in general. Identification of brain commands through EEG signals is exciting and endless research. Although it can be done by considering a single variable, the use of multi variables is inevitable. Emotion or concentration can induce motor imagery when imagining commands. In future work, it is necessary to consider 2D CNN in combination with either parallel or serial RNN.

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