



The Effect of Changing Convolutional Neural Nets Parameters on EEG Signals Recognition Ratio

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Abstract

Brain Computer Interface (BCI), especially systems for recognizing brain signals using EEG (Electroencephalography), is one of the important research topics that arouse the interest of many researchers currently. Convolutional Neural Nets (CNN) is one of the most important deep learning classifiers used in this recognition process, but the parameters of this classifier have not yet been precisely defined so that it gives the highest recognition rate and the lowest possible training and recognition time. This research proposes a system for recognizing EEG signals using the CNN network, while studying the effect of changing the parameters of this network on the recognition rate, training time, and recognition time of brain signals, as a result the proposed recognition system was achieved 76.38 % recognition rate, And the reduction of classifier training time (3 seconds) by using Common Spatial Pattern (CSP) in the preprocessing of IV2b dataset, and a recognition rate of 76.533% was reached by adding a layer to the proposed classifier.

Keywords: CNN; EEG; Signals; Recognition ratio

1. Introduction

The brain controls most of the body's activities, such as processing, integrating and coordinating the information it receives from the sensory organs, and makes decisions regarding the generalizations sent to the rest of the body's organs. The brain is located inside the skull and is protected by it. The cerebrum is the largest part of the human brain; it consists of two cerebral hemispheres. The cerebral cortex consists of six neural layers, while the parietal cortex consists of only three or four layers. Although the left and right cerebral hemispheres are very similar in shape and functions, some functions are related to one side of it, such as language in the left cleft and visual and spatial ability in the right cleft. This research is considered a combination of brain-computer interface and artificial intelligence.

2. Previous studies

Many studies have been conducted in order to recognize brain signals using artificial intelligence, where a number of researchers in [1] presented a study to recognize brain signals using a local dataset consisting of 21,700 EEG brain signals and FBCSP (filter bank CSP) was used with a variable number of filters in primary processing and CNN network as a classifier, the average recognition rate was (74.15%) with an error rate ($\pm 15\%$) at 3*3 (Kernel) and a number of filters 10.

A study was also conducted to identify brain signals expressing actual hand movement and motor perception (imagine hand movement) using the algorithm (Linear Discriminant Analysis) LDA for classification and CSP in primary processing, using a protected database, where the muscle signals of the hand were recorded synchronously with the brain signals EEG, converting the muscle signals into a matrix of zeros and ones of size 6*30 and stored as a dataset,

and then training the classifier LDA to recognize the EEG signals by converting them into a matrix binary the same size and compare it with the dataset. The recognition rate was $63.98 \pm 7.54\%$ on actual movement and $46.96 \pm 15.3\%$ on motor perception [2].

A study was also presented to identify brain signals using the CNN network as a classifier and the database used (finger), where this dataset contains EEG signals expressing real movement of the fingers of one hand individually, ten people participated in the recording with a recording frequency of 1000Hz and a percentage of 80% was reached using SVM (Support Vector Machine) as a classifier[3].

Another study was conducted to identify EEG signals, in which the Gan (Generative Adversarial Networks) Network was used to add fake samples to the dataset, the CNN classifier also used four bypass layers and two Max pooling layers, and a recognition ratio of 15.86 ± 67.97 was reached on the IV2b dataset when 300 fake samples were added to the dataset [4].

It should be noted that the performance assessment should be carried out on the same data set, the use of a specific kernel for the CNN classificatory gives different results depending on the data set used.

It is noted from the results obtained in these researches that they cannot be generalized to all databases and workbooks, as the parameters used in these researches do not necessarily give the best performance, so it is necessary to study the impact of changing the parameters of the workbook on the recognition ratio, training and recognition times.

3. The importance of research and its goals

The importance of the research lies in the fact that increasing the recognition rate contributes to the application of motor perception systems in practice, and therefore contributes to finding solutions for amputee limb owners, when recognizing the movement imagined in the brain, commands can be directed from the brain to these limbs and executed by means of a robotic prosthesis. In this research, an EEG signal recognition system is being built using the CNN network and the effect of changing the parameters of this network on the recognition ratio is being studied.

4. Research methods and modality

Initially, the brain signals are loaded chronologically and spectrally, and then the pre-processing process is applied and the relationship between the nature of the EEG brain signals and the coefficients of the CNN classifier used is discovered, after which the effect of the calibration of these coefficients on the recognition ratio is studied. The data set used in this research is Iv2b, in order to test the performance of the proposed classifier. Working within an environment Google Collaborator.

An electroencephalogram (EEG) is a multichannel time series that captures the electrical activity recorded from the scalp from specific locations by electrodes as shown in Figure 1.

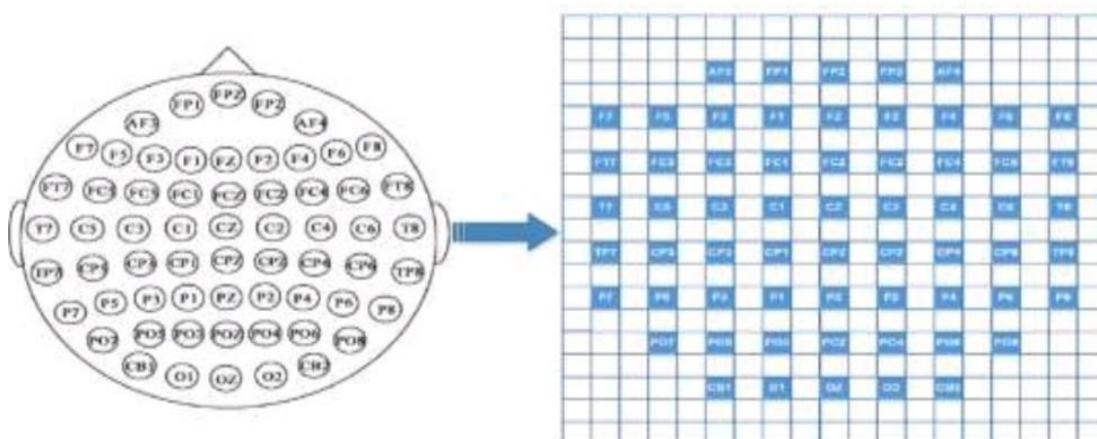


Figure 1. The locations of the electrodes for recording EEG signals [4].

EEG signal recording systems usually use electrodes each connected to a single wire, where the locations and names of the electrodes are determined through a global 20-10 system, which ensures the standardization of electrode names in all laboratories.

4.1. The database used

The database (BCI Competition IV2b) was used and consists of data for 9 participants, containing 6520 motion visualizations. The brain signals were recorded using three EEG electrodes: C3, Cz and C4, with a cutting frequency of 250Hz, and the signal was passed through a packet pass filter (0.5 Hz-100Hz)

The database contains two types of motor visualization, the first is imagining moving the right hand and the second is imagining moving the left hand, Figure 2 shows a drawing of one motor visualization from the iv2b database.

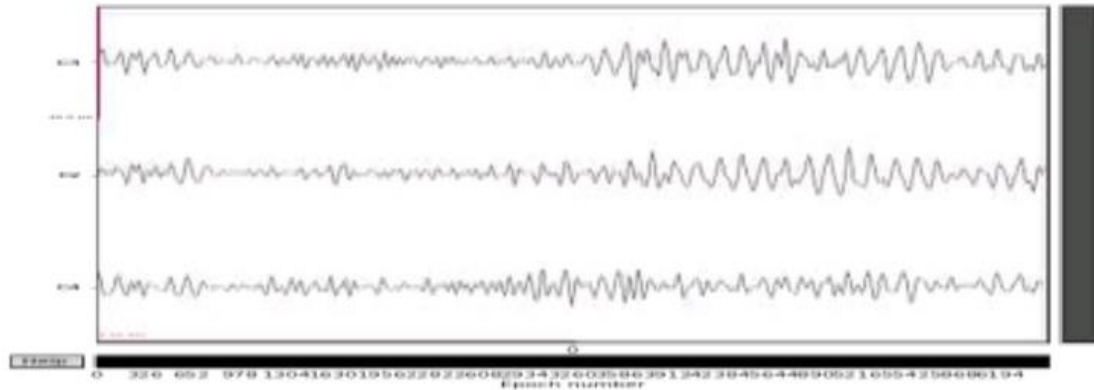


Figure 2. A random sample from the IV2b database.

4.1.1. Common Spatial Pattern

The CSP idea is based on the use of a set of linear transformations to increase the contrast between the target varieties, by moving to a new space (CSP), where the matrix of mutual variation between varieties is calculated and then the conversion matrix is calculated, applying filters that give the highest contrast between varieties, Figure 3 shows the signal before and after applying CSP.

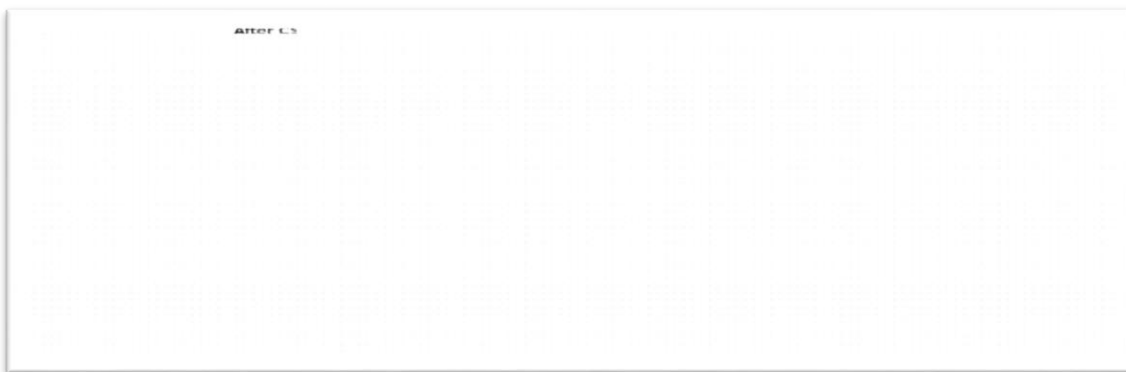


Figure 3. The signal before and after the application of the common spatial pattern

Let x_1 and x_2 be two windows of a multichannel signal, the CSP algorithm determines the component w^T so that the contrast ratio between the two windows is maximized according to relation (1) [5]:

$$w = \operatorname{argmax}_w \frac{\|wX_1\|^2}{\|wX_2\|^2} \quad (1)$$

The CSP method can be applied to multichannel signals in general, it is commonly found in the application to electroencephalogram (EEG) signals in particular, Figure 4 shows EEG brain signals. After applying the combined spatial pattern CSP with four filters to the EEGBCI database, we note that the filter CSP2 gives the greatest contrast between varieties and the ruler next to the figure shows the value of the spectral activity expressed for each color gradient.

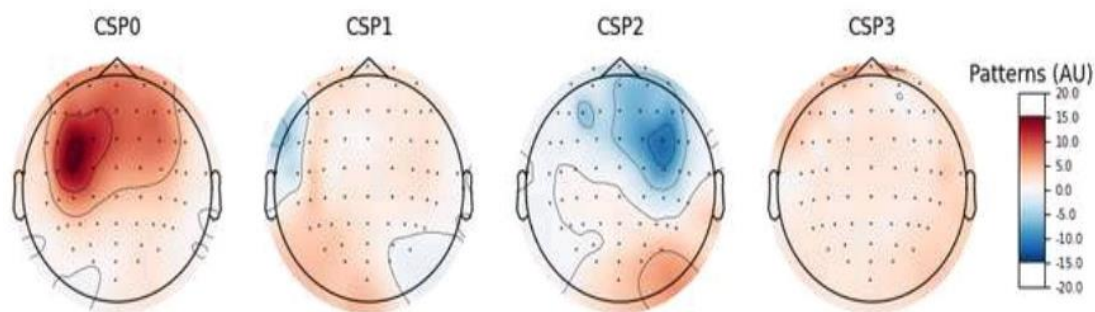


Figure 4. Electroencephalogram spectroscopically when using CSP.

The use of CSP in the time domain results in a matrix with dimensions (11,26,3,1) for each motion perception in the IV2b dataset, while in the spectral domain it produces a matrix (3,3,1) which does not fit the nature of the classifier CNN.

4.1.2. Workbook construction

The classifier was built using a CNN network consisting of the following layers: two convolutional layers(Conv2D), then an assembly layer (Average pooling), followed by a flattening layer (Flatten) and two condensation layers(Dense) (i.e., two fully connected interconnection layers), the first consisting of 80 neurons, and the second, which is the output layer consisting of two neurons. As shown in Figure 5.

The input of the CNN network is the brain signals after converting them to a matrix, each repetition or motion perception (Epoch) is a digital matrix with dimensions (3, 1126, 1), where 3 is the number of recording channels or electrodes and 1126 the number of time samples per channel, and Figure 5 shows the input and output of each layer in the workbook when the number of filters is 40 filters per layer.

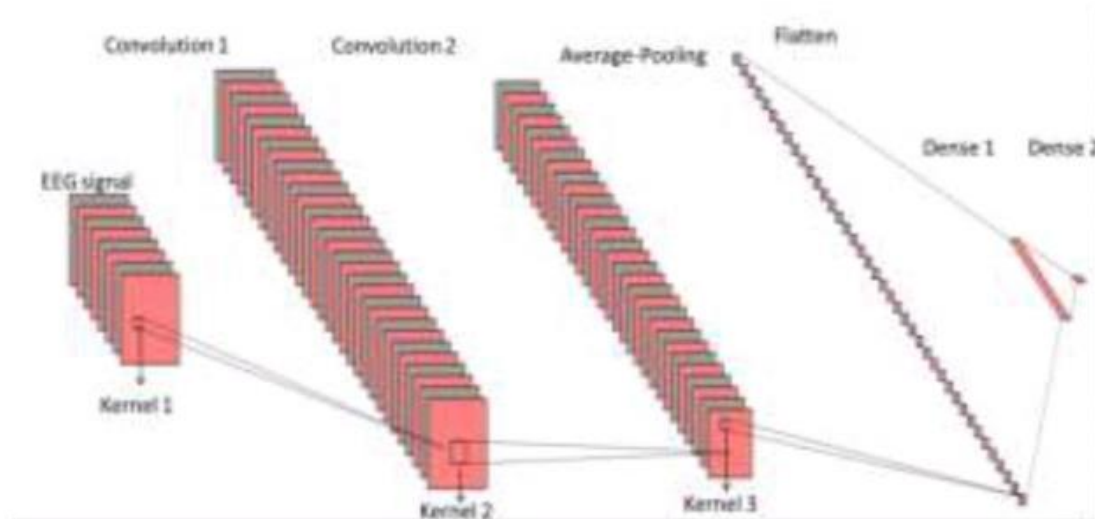


Figure 5. The proposed CNN network.

Table 1 shows the input and output of each layer in the CNN network proposed in experiment No. 4 of the second scenario, and also shows the number of transactions resulting from each layer and the total number of transactions, and the number of these transactions changes significantly with the change of the kernel for each layer, as the number of transactions in this research ranges between 200,000 and 2,200,000.

The Parameters in the table indicate the weight and other changes that are adjusted during the network training and testing process, through which the complexity of the workbook can be estimated.

Table 1: the values of income, output and transactions resulting from each layer in experiment 4 of the second scenario.

Layer	Layer type	Kernel	Output shape	Parameters	Activation Fn
1	Conv2d	20,1	(None,1126,3,40)	840	Relu
2	Conv2d	1,3	(None,1126,3,40)	4840	Relu
3	Average_pooling2d	100,1	(None,21,3,40)	0	-
4	Flatten	-	(None,2520)	0	-
5	Dense1	-	(None,80)	201860	Relu
6	Dense2	-	(None,2)	162	Softmax
Total parameters		207522			
Trainable Parameters		207522			
None Trainable Parameters		0			
Optimizer: Adam, Model: Sequential, Patch size: 32					

4.2. Performance evaluation criteria

The performance of the proposed classifier is evaluated by measuring the accuracy and the area under the AUC curve, which is the most important criterion in measuring the accuracy of recognition when there are only two classifiers. Calculated by relation (2) [10].

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \quad (2)$$

True Positive (TP): positive integer States, **True Negative (TN):** negative integer states, **False Positive (FP):** positive integer states, **False Negative (FN):** negative integer States and these values are obtained from the confusion matrix shown in the results of the scenarios.

The area under the ROC curve (AUC):

The (Area Under the Roc Curve) AUC is an important criterion for evaluating works, as it measures the degree of confidence in the workbook based on the Receiver Operating Characteristic Curve ROC, as the ROC curve describes the performance of the workbook according to different thresholds, to draw this curve we consider the rate of positive correct cases (TPR) is the Y axis and the rate of positive false cases (FPR) is the X axis, and the upper left corner represents the ideal case. The AUC value ranges from (0) as the worst performer to (1) as the best performer as shown in Figure 6.

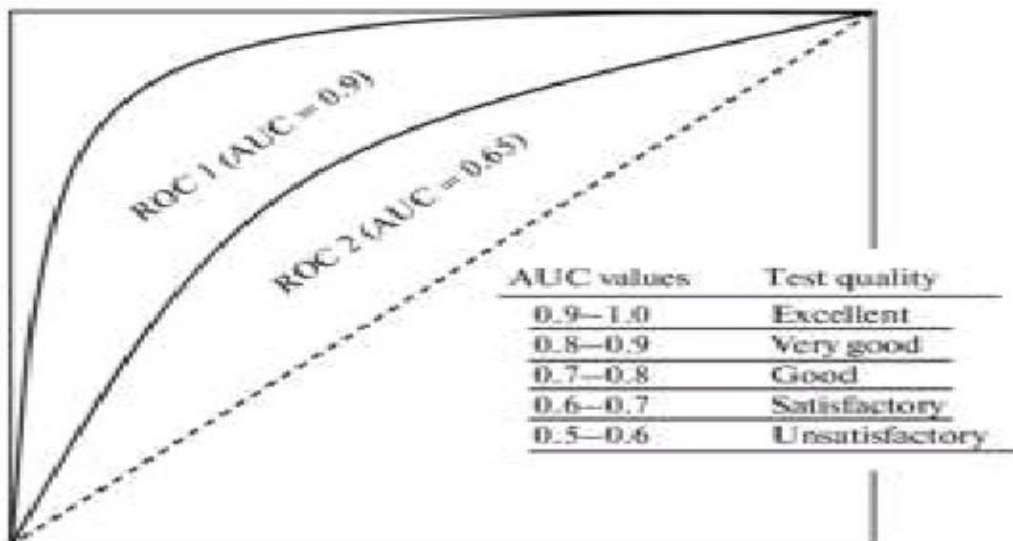


Figure 6. The AUC criterion based on the ROC curve [11]

As for the time, it is divided into two parts: **the training time**, which is the time needed to train the workbook, and **the test time**, which is the time needed to test the proposed system.

Business scenarios:

The work was carried out according to 3 different scenarios, 80% of IV2b datasets were used in the training process and 20% in the testing process.

The first scenario was in which the CNN network was tested with changing some parameters until reaching the best performance to study the effect of changing parameters on performance, and **the second scenario**, CSP was applied in signal preprocessing with the use of the network with the parameters that gave the best performance in the first scenario to study the feasibility of using CSP in the time domain.

The third scenario, we studied the effect of adding layers on the recognition ratio and time cost, by adding a (Conv2d) wrapping layer between the first and second layer.

The CNN network parameters that have been changed in the proposed scenarios are the kernel of the first layer Kernel 1, the kernel of the second layer Kernel 2, the kernel of the third layer Kernel 3 and the Stride step in the Average pooling layer.

5. Results and discussion

In this research, work was carried out on the google colab platform to conduct simulations in terms of designing and testing the proposed system, the python3 version, using 12.7 GB RAM and a GPU graphics processor with 15 GB memory and a storage size of 78.2 B.

The first scenario

11 experiments were conducted using different cores for each layer in the CNN network, testing the network performance on the IV2b database in terms of recognition ratio, training and recognition times and the AUC standard. Increasing the size of the kernel results in an increase in the time cost, and to avoid this increase, we enlarge the Stride step in the Average pooling layer, where the Stride indicates the step that the kernel is walking, and the larger it is, it reduces the output from said Layer.

It is noted from Table 2 that the best results were when using kernel (35,1) for the first layer and (1,3) for the second layer with a percentage of 76.38%, and the worst performance was when using kernel (3,3) for the first layer and (3,3) for the second layer with a percentage of 65.439%. The difference between the best and worst performance achieved is 10.941% in terms of recognition percentage and (14.615 Seconds) in terms of training time. It is also noted that the 3, 3 kernel gave the worst ratio known using the proposed classifier and the iv2b database.

Table 2: The effect of changing the coefficients of the CNN classifier on the recognition ratio.

ACU	recognition ratio	test time (ms)	training time (sec)	classifier coefficients				experiment number
				Stride	Kernel 3	Kernel 2	Kernel 1	
0.6797	0.65439	3	90.194	1,1	3,3	3,3	3,3	1
0.70686	0.67177	3	87.399	1,1	3,1	1,3	3,1	2
0.70901	0.67586	4	101.332	1,1	5,1	1,5	5,1	3
0.75120	0.71932	5	109.739	5,1	10,1	1,10	10,1	4
0.74439	0.71012	6	204.263	10,1	20,1	1,20	20,1	5
0.77754	0.72034	7	204.700	15,1	30,1	1,25	25,1	6
0.78729	0.74693	7	204.990	25,1	50,1	1,25	25,1	7
0.79889	0.73926	3	84.221	50,1	100,1	1,3	25,1	8
0.80430	0.75255	3	84.659	50,1	100,1	1,3	30,1	9
0.81480	0.76380	3	75.579	50,1	100,1	1,3	35,1	10
0.80871	0.75511	3	71.811	50,1	100,1	1,3	40,1	11

The second scenario

6 experiments were conducted in which we used the CSP combined spatial pattern in the process of data preprocessing and changing the classifier coefficients to obtain the results shown in Table 3, where it is noted that the best performance when using CSP in primary processing with a mask of 35.1 in the first layer and 1.3 in the second with a recognition rate of 76.022%, which means, the use of CSP did not significantly affect performance in terms of recognition percentage, but the training time is four seconds less on average. It was found that the use of a circular mask (3, 3) gave the worst performance by a percentage of 72.903% compared to the use of a one-dimensional mask.

Table 3: The effect of changing the coefficients of the CNN classifier on the recognition ratio when using CSP in primary processing.

ACU	recognition ratio	test time (ms)	training time (Seconds)	classifier coefficients				experiment number
				Stride	Kernel 3	Kernel 2	Kernel 1	
0.80698	0.75664	4	71.792	50,1	100,1	1,3	35,1	1
0.80492	0.74846	4	71.783	50,1	100,1	1,3	30,1	2
0.80635	0.75306	4	71.634	50,1	100,1	1,3	25,1	3
0.80605	0.76022	3	71.564	50,1	100,1	1,3	20,1	4
0.79759	0.74130	4	75.739	50,1	100,1	1,3	15,1	5
0.79022	0.72903	5	108,117	50,1	100,1	3,3	5,1	6

The third scenario

We added conv2d convolution layer to CNN network to study the effect of adding a layer on the network performance, where we conducted two experiments and changed the core in each experiment as shown in Table 4.

Table 4: the effect of changing the parameters of the CNN classifier on the recognition ratio when adding a new layer.

ACU	recognition ratio	test time (ms)	training time (Seconds)	Stride	classifier coefficients				experiment number
					Kernel 3	Kernel 2	Kernel added	Kernel 1	
0.81060	0.76175	7	250.213	50,1	100,1	1,3	10,1	35,1	1
0.80581	0.76533	7	265.177	50,1	100,1	10,3	25,1	50,1	2

It can be seen from Table (4) that the thoughtful addition of a layer to the classifier led to a slight improvement in the recognition percentage (0.2%) compared to the best case in the first scenario, but an increase in the test time (4 ms), that is, almost doubled, and an increase in the training time (189.598 Sec). Figure 7 shows how the samples were identified based on the confusion matrix.

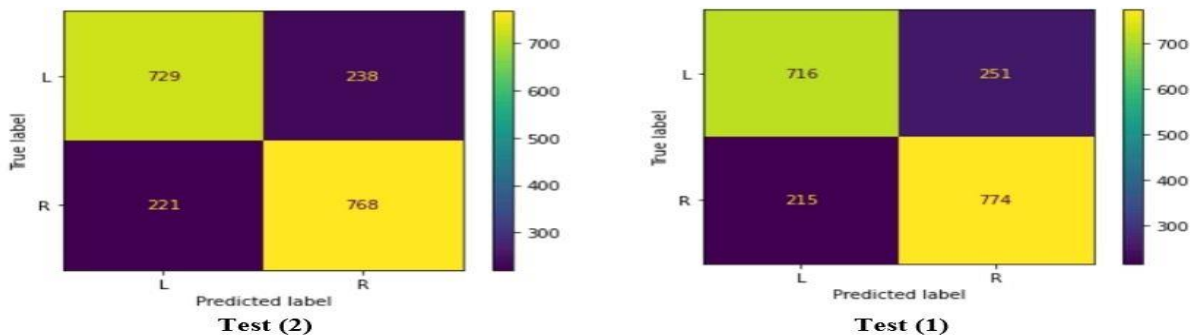


Figure 7. Recognition results in the third scenario based on the confusion matrix.

Conclusion

The use of a horizontal mask (m, 1) in the first layer of the workbook, and a vertical mask (1, n) in the second layer where n is equal to the number of channels or sensors improved the recognition percentage (%11.1)

The use of the common spatial pattern (CSP) in the time domain with the classifier CNN has no noticeable effect on the recognition ratio, and its use in the spectral domain does not fit the nature of the classifier CNN but can be used with other classifiers such as (Support Vector Machine) SVM.

Adding layers to the workbook also increases the recognition percentage, but this is done at the expense of significantly increasing the training and recognition time, while not being able to significantly improve performance. After studying and analyzing the results, we propose the following:

- Using CNN hybrids with other classifiers such as random Forest Classifier.
- Increase the initial processing processes and the use of algorithms commensurate with the nature of the CNN workbook.
- Using famous workbooks such as Google net and Alex net after processing brain signals to become suitable for these networks.

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