

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 achieved a 76.38% recognition rate and reduced classifier training time by 3 seconds by using Common Spatial Pattern (CSP) in preprocessing the IV2b dataset. 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. A number of researchers in [1] presented a study to recognize brain signals using a local dataset consisting of 21,700 EEG brain signals. FBCSP (filter bank CSP) was used with a variable number of filters in primary processing and a CNN network as a classifier. The average recognition rate was 74.15% with an error rate of $\pm 15\%$ at a 3×3 kernel and 10 filters.

A study was also conducted to identify brain signals expressing actual hand movement and motor perception (imagined hand movement) using Linear Discriminant Analysis (LDA) for classification and CSP in primary processing, using a protected database. The muscle signals of the hand were recorded synchronously with the EEG brain signals, converted into a binary matrix of size 6×30 , and stored as a

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

Another study was presented to identify brain signals using a CNN network as a classifier and the Finger dataset. 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 1000 Hz, and a rate of 80% was reached using a Support Vector Machine (SVM) as a classifier [3].

Another study was conducted to identify EEG signals, in which a Generative Adversarial Network (GAN) 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 $67.97 \pm 15.86\%$ was reached on the IV2b dataset when 300 fake samples were added [4].

It should be noted that performance assessment should be carried out on the same dataset; the use of a specific kernel for the CNN classifier gives different results depending on the dataset used.

The results obtained in these studies cannot be generalized to all databases and classifiers, as the parameters used do not necessarily give the best performance. It is therefore necessary to study the impact of changing classifier parameters on the recognition ratio and on training and recognition times.

3. THE IMPORTANCE OF THE RESEARCH AND ITS GOALS

The importance of the research lies in the fact that increasing the recognition rate contributes to the practical application of motor perception systems and therefore contributes to finding solutions for amputees. When the movement imagined in the brain is recognized, commands can be directed from the brain to robotic prosthetic limbs and executed. In this research, an EEG signal recognition system is built using a CNN network, and the effect of changing the parameters of this network on the recognition ratio is studied.

4. RESEARCH METHODS AND MODALITY

Initially, the brain signals are loaded chronologically and spectrally. The preprocessing process is then applied, and the relationship between the nature of the EEG brain signals and the coefficients of the CNN classifier is explored. Afterward, the effect of calibrating these coefficients on the recognition ratio is studied. The IV2b dataset is used to test the performance of the proposed classifier. The work was performed within the Google Colaboratory environment.

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

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

4.1 The Database Used

The BCI Competition IV2b database was used. It consists of data for 9 participants and contains 6,520 motor-imagery trials. Brain signals were recorded using three EEG electrodes, C3, Cz, and C4, at a sampling frequency of 250 Hz, and the signal was passed through a band-pass filter from 0.5 to 100 Hz.

The database contains two types of motor imagery: imagining movement of the right hand and imagining movement of the left hand. Figure 2 shows one motor-imagery sample from the IV2b database.

4.1.1 Common Spatial Pattern

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

Let $\mathbf{X}_1$ and $\mathbf{X}_2$ be two windows of a multichannel signal. The CSP algorithm determines the component $\mathbf{w}^T$ so that the contrast ratio between the two windows is maximized according to [5]:

$$\mathbf{w} = \arg \max_{\mathbf{w}} \frac{\|\mathbf{w}\mathbf{X}_1\|^2}{\|\mathbf{w}\mathbf{X}_2\|^2}. \quad (1)$$

The CSP method can be applied to multichannel signals in general and is commonly applied to EEG signals in particular. Figure 4 shows EEG brain signals after applying CSP with four filters to the EEGBCI database. The CSP2 filter gives the greatest contrast between classes, and the scale next to the figure shows the spectral-activity value represented by each color gradient.

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

4.1.2 Classifier Construction

The classifier was built using a CNN consisting of two convolutional layers (Conv2D), an average-pooling layer, a flattening layer, and two dense layers (i.e., two fully connected layers). The first dense layer consists of 80 neurons, and the second, which is the output layer, consists of two neurons, as shown in Figure 5.

The input to the CNN is the brain signal after conversion to a matrix. Each repetition or motor-imagery epoch is a digital matrix with dimensions (3, 1126, 1), where 3 is the number of recording channels or electrodes and 1126 is the number of time samples per channel. Figure 5 shows the input and output of each classifier layer when 40 filters are used per layer.

Table 1 shows the input and output of each layer in the CNN proposed in Experiment 4 of the second scenario. It also shows the number of parameters produced by each layer and the total number of parameters. This number changes

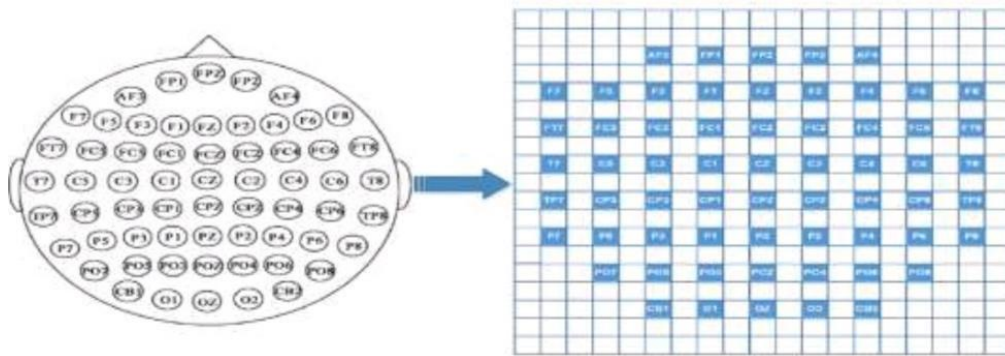


Figure 1. The locations of the electrodes for recording EEG signals [4].

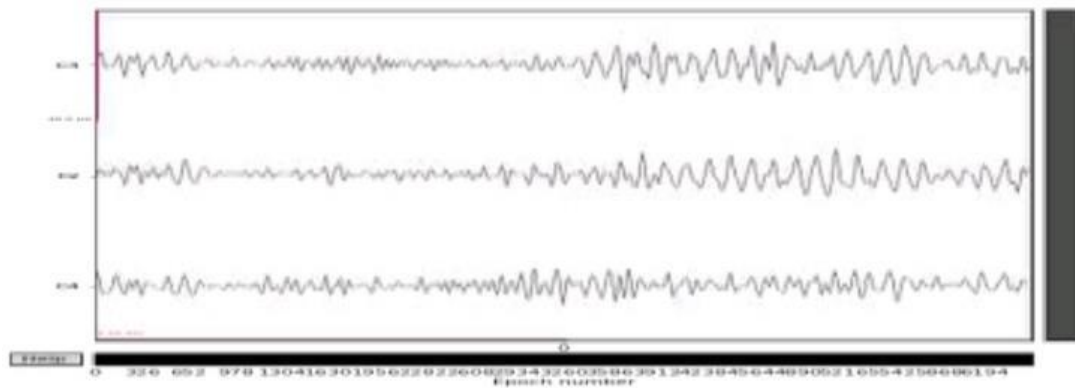


Figure 2. A random sample from the IV2b database.

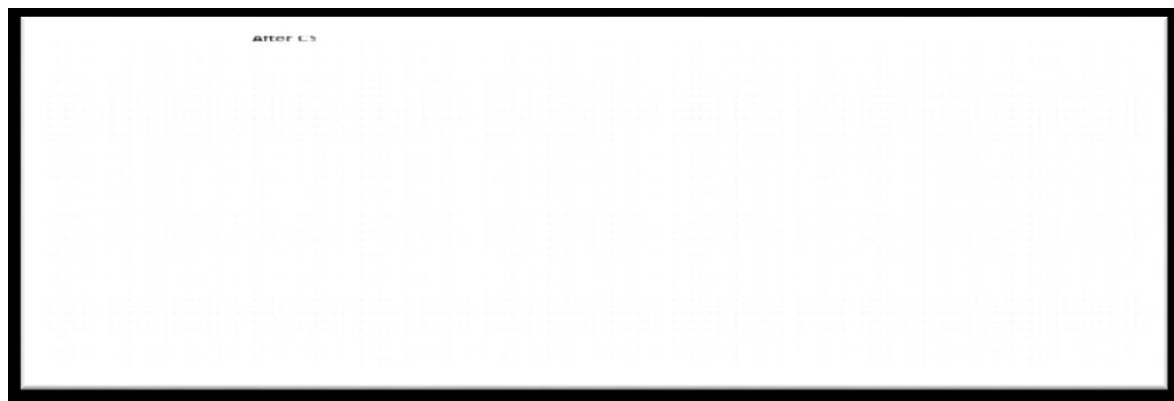


Figure 3. The signal before and after the application of the common spatial pattern.

significantly with the kernel of each layer, ranging in this research from 200,000 to 2,200,000. The parameters indicate the weights and other values adjusted during network training and testing, through which classifier complexity can be estimated.

4.2 Performance Evaluation Criteria

The performance of the proposed classifier is evaluated by measuring accuracy and the area under the AUC curve, which is one of the most important criteria for measuring recognition accuracy when there are only two classes. Accuracy is calculated by [10]:

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

True Positive (TP) denotes positive instances classified cor-

rectly; **True Negative (TN)** denotes negative instances classified correctly; **False Positive (FP)** denotes negative instances classified as positive; and **False Negative (FN)** denotes positive instances classified as negative. These values are obtained from the confusion matrix shown in the scenario results.

Area under the ROC curve (AUC): AUC is an important criterion for evaluating classifiers, as it measures confidence in the classifier based on the Receiver Operating Characteristic (ROC) curve. The ROC curve describes classifier performance at different thresholds. The true-positive rate (TPR) is placed on the y-axis and the false-positive rate (FPR) on the x-axis; the upper-left corner represents the ideal case. The AUC value ranges from 0 for the worst performer to 1 for the best performer, as shown in Figure 6.

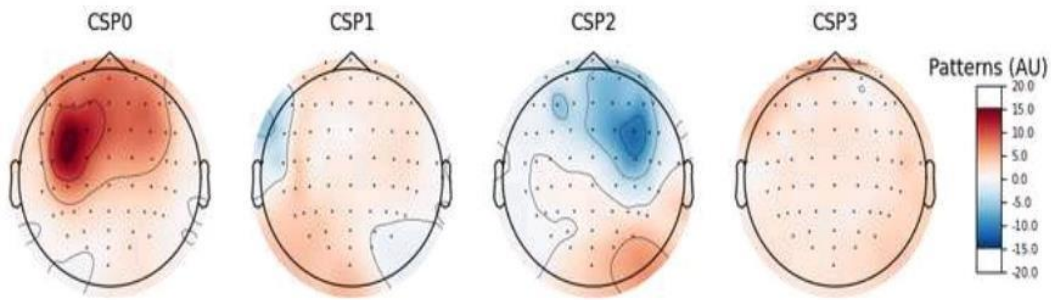


Figure 4. Electroencephalogram spectroscopically when using CSP.

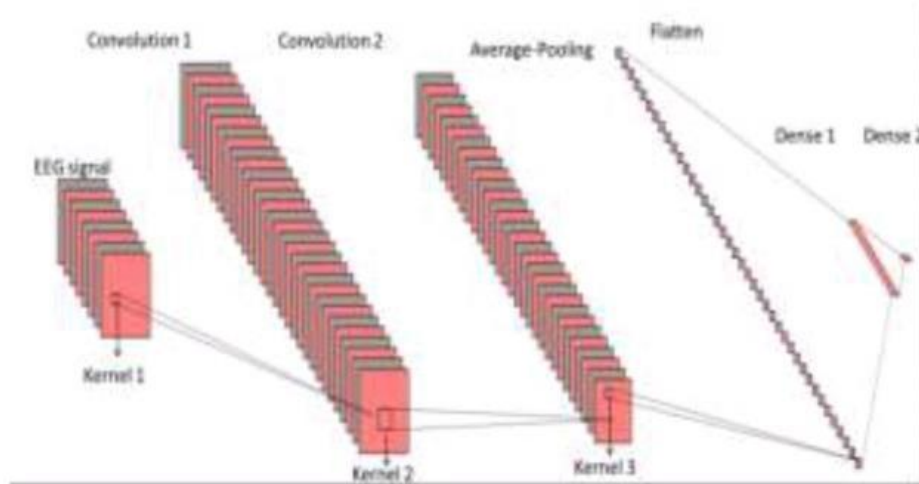


Figure 5. The proposed CNN network.

Table 1. The values of input, output, and parameters 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)	4,840	ReLU
3	Average_pooling2d	100, 1	(None, 21, 3, 40)	0	–
4	Flatten	–	(None, 2520)	0	–
5	Dense1	–	(None, 80)	201,860	ReLU
6	Dense2	–	(None, 2)	162	Softmax
Total parameters			207,522		
Trainable parameters			207,522		
Non-trainable parameters			0		
Optimizer: Adam; Model: Sequential; Batch size: 32					

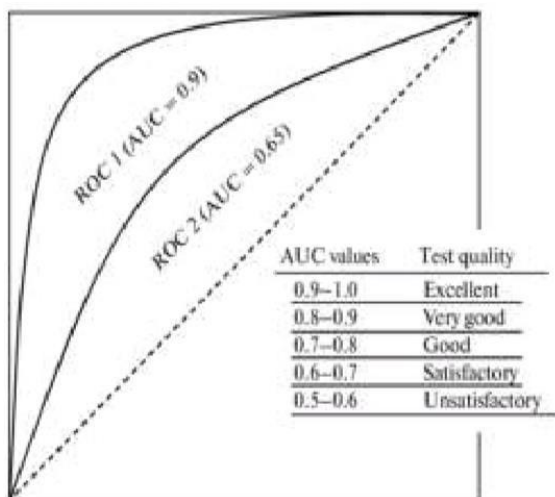


Figure 6. The AUC criterion based on the ROC curve [11].

Time is divided into two parts: **training time**, which is the time needed to train the classifier, and **test time**, which is the time needed to test the proposed system.

Experimental scenarios: The work was carried out according to three different scenarios. In all scenarios, 80% of the IV2b dataset was used for training and 20% for testing.

In the **first scenario**, the CNN network was tested while changing selected parameters until the best performance was reached, in order to study the effect of parameter changes on performance. In the **second scenario**, CSP was applied during signal preprocessing, and the network parameters that gave the best performance in the first scenario were used to study the feasibility of CSP in the time domain. In the **third scenario**, the effect of adding layers on the recognition ratio and time cost was studied by adding a Conv2D layer between

the first and second layers.

The CNN parameters 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 in the average-pooling layer.

5. RESULTS AND DISCUSSION

The simulations for designing and testing the proposed system were conducted on the Google Colab platform using Python 3, 12.7 GB of RAM, a GPU with 15 GB of memory, and 78.2 GB of storage.

The First Scenario

Eleven experiments were conducted using different kernels for each layer of the CNN, testing network performance on the IV2b database in terms of recognition ratio, training and recognition times, and the AUC criterion. Increasing the kernel size increases the time cost. To limit this increase, the stride in the average-pooling layer was enlarged. The stride indicates the step taken by the kernel; increasing it reduces the output of that layer.

Table 2 shows that the best result was obtained with kernel (35, 1) in the first layer and (1, 3) in the second layer, yielding 76.38%. The worst performance was obtained with kernel (3, 3) in the first layer and (3, 3) in the second layer, yielding 65.439%. The difference between the best and worst performance was 10.941 percentage points in recognition ratio and 14.615 seconds in training time. The 3×3 kernel produced the worst recognition ratio with the proposed classifier on the IV2b database.

The Second Scenario

Six experiments were conducted using CSP in data preprocessing and changing the classifier coefficients to obtain the results shown in Table 3. The best performance using CSP in primary processing was obtained with a (35, 1) kernel in the first layer and a (1, 3) kernel in the second, with a recognition rate of 76.022%. Thus, CSP did not significantly affect recognition performance, but reduced training time by four seconds on average. A circular (3, 3) kernel gave the worst performance, at 72.903%, compared with a one-dimensional kernel.

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

AUC	Recognition	Test time	Training time	Classifier coefficients				Experiment
				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

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

AUC	Recognition	Test time	Training time	Classifier coefficients				Experiment
				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

A Conv2D layer was added to the CNN to study the effect of adding a layer on network performance. Two experiments

were conducted, and the kernel was changed in each experiment, as shown in Table 4.

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

AUC	Recognition	Test time	Training time	Classifier coefficients					Experiment
				Stride	Kernel 3	Kernel 2	Added kernel	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

Table 4 shows that the considered addition of a layer to the classifier led to a slight improvement of 0.2% in the recog-

nition ratio compared with the best case in the first scenario. However, the test time increased by 4 ms, almost doubling,

and the training time increased by 189.598 s. Figure 7 shows

how samples were identified based on the confusion matrix.

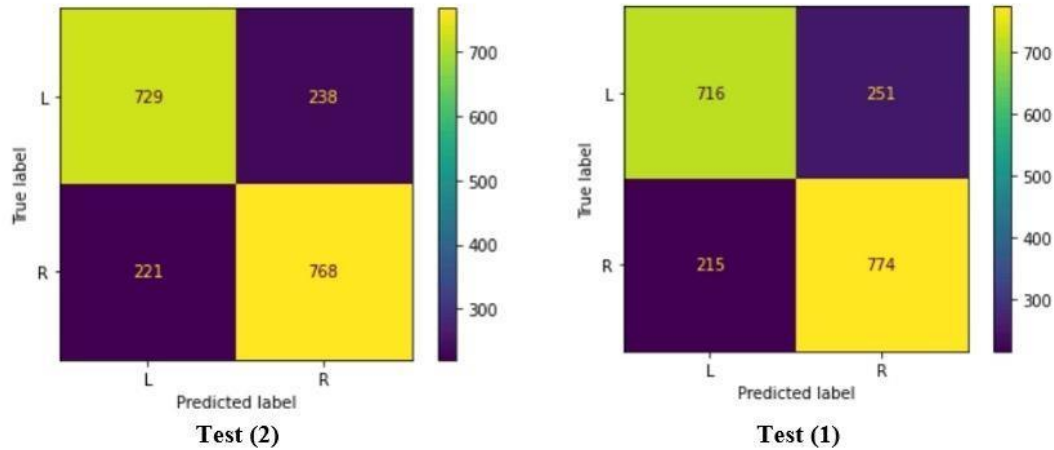


Figure 7. Recognition results in the third scenario based on the confusion matrix.

6. CONCLUSION

The use of a horizontal kernel ($m, 1$) in the first classifier layer and a vertical kernel ($1, n$) in the second layer, where n equals the number of channels or sensors, improved the recognition ratio by 11.1%.

The use of Common Spatial Pattern (CSP) in the time domain with the CNN classifier had no noticeable effect on the recognition ratio. Its use in the spectral domain does not fit the nature of the CNN classifier, but it can be used with other classifiers such as a Support Vector Machine (SVM).

Adding layers to the classifier also increases the recognition ratio, but at the expense of significantly increased training and recognition times, without a substantial performance improvement. After studying and analyzing the results, the following directions are proposed:

- Use CNN hybrids with other classifiers, such as a Random Forest classifier.
- Increase preprocessing and use algorithms compatible with the nature of the CNN classifier.
- Use well-known classifiers such as GoogLeNet and AlexNet after processing the brain signals to make them suitable for these networks.

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