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Research on recognition accuracy and overfitting of brain-computer interface based on convolutional neural network model

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Abstract: *This paper investigates several machine learning methods employed in brain-computer interface applications and focuses on their use in addressing overfitting and improving prediction accuracy. Firstly, the concept of L2 regularization and its role in model training are introduced, which effectively reduces the problem of overfitting by controlling the model complexity. Then, the application of convolutional neural network (CNN) in visual image analysis is introduced in detail, emphasizing that it effectively reduces the number of parameters through local receptive field, weight sharing and pooling layer, and alleviates the overfitting of the model. Then the ensemble idea of random forest algorithm and its application in classification and regression are discussed, especially how to use randomness to improve the prediction accuracy in the process of processing multiple decision trees. Finally, the performance of different algorithms on actual data sets is analyzed, and it is pointed out that convolutional neural network has more outstanding performance in recognition accuracy than support vector machine and random forest, especially in complex signal discrimination and individual difference processing.*

Keywords: *Convolutional neural network model, recognition accuracy of brain-computer interface, overfitting*

1. Introduction

Under the background of the rapid development of brain-computer interface (BCI) technology, it is becoming increasingly important to use machine learning and neural network to solve the problem of brain signal recognition. Brain-computer interface technology aims to realize the interaction with computer or external devices by analyzing EEG signals, which provides an important communication mode and control means for individuals with limited mobility. However, due to the complexity of EEG signals and the differences between individuals, how to effectively identify and classify these signals is still a challenging problem. At present, convolutional neural network (CNN)[1], as a powerful machine learning tool, has shown excellent performance in image and speech recognition and other fields. It can effectively capture the spatial and temporal characteristics of data, which makes it have broad application prospects in processing EEG signal recognition tasks. This study aims to explore the recognition accuracy of brain-computer interfaces based on convolutional neural network models and compare them with traditional methods to evaluate their potential in improving recognition accuracy and reducing overfitting. By establishing and optimizing CNN model[2], this paper attempts to solve the key problems in brain-computer interface system, so as to provide theoretical and practical guidance for the development of more reliable and efficient brain-computer interface technology in the future.

2. Data processing

The human body is a complex organism, and the physiological process is affected by many non-human control factors. EEG signals are bioelectrical signals collected on the scalp surface through electrodes to reflect the internal state of the brain. However, in the process of EEG acquisition, it is inevitable to introduce various artifacts and interference that do not come from brain nerve cells. For

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example, ophthalmic electromyography, electrocardiogram, power frequency dry interference, etc., especially ophthalmic interference, has a large amplitude, and the waveform of ophthalmic signal is shown in the figure below. However, the specific EEG signal to be analyzed usually has a small amplitude, so the non-stationarity characteristics of EEG signal are prominent under the interference of other signals[3]. Therefore, certain preprocessing is needed before the classification and recognition of targets[4]. In the process of research, the data collected by 20 signal channels are detrending and filtered to make the signal output more stable and convenient for further analysis, as shown in Figure 1:

Figure 1: Waveform of eye electrical signal

Considering that the brain-computer interface may cause data deviation when obtaining data, deleting the trend from the data can better focus the analysis on the fluctuation of the data trend itself[5]. Data detrending is to subtract an optimal (least squares) fitting line, plane or surface from the data[6], so that the mean value of the detrending data is zero. Therefore, before analyzing the problem, we use Matlab software to Detrend the data, and use detrend function to perform primary function fitting and quadratic function fitting respectively to analyze the effect. We compare the results before and after detrending the data collected by channel 1 and Channel 11 respectively. The situation of channel 1 is shown in Figure2. We find that compared with the initial data, the fluctuation degree of the signal graph obtained by detrending is still large, so the effect of detrending is not great[7]. Therefore, detrending is omitted in the process of data processing[8].In the process of EEG signal acquisition, it will be affected by surrounding noise and power frequency noise, so in order to obtain stable EEG signal output, it is necessary to filter the noise of the original signal, and use the bandpass filter to take out the signal between 1Hz-20Hz frequency[9]. Filtering processing is mainly with the help of eeglab software, the main operation process is as follows:On the eeglab interface, select Tools > Filter the data > Basic FIR filter, enter 1Hz as the lower edge frequency, 20Hz as the upper edge frequency, and click "OK". The parameter design process is shown in Figure 2 below:

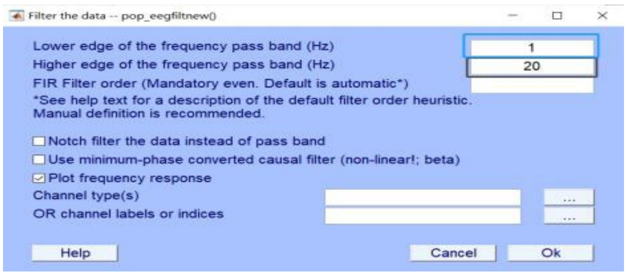

Figure 2: Parameter design of Filter the data method on eeglab interface

After the above operations, the comparison chart of the collected signals of 20 channels of char06 (Q) in S1_train_data before and after filtering is shown below. Before filtering, due to the large difference in the value range of different channels, all the signal data of channels cannot be displayed in one chart, so the stationarity and other characteristics of signals cannot be judged[10]. After filtering, the signal data of all channels are more clear and obvious, which is conducive to further feature judgment,this is shown in Figure 3.

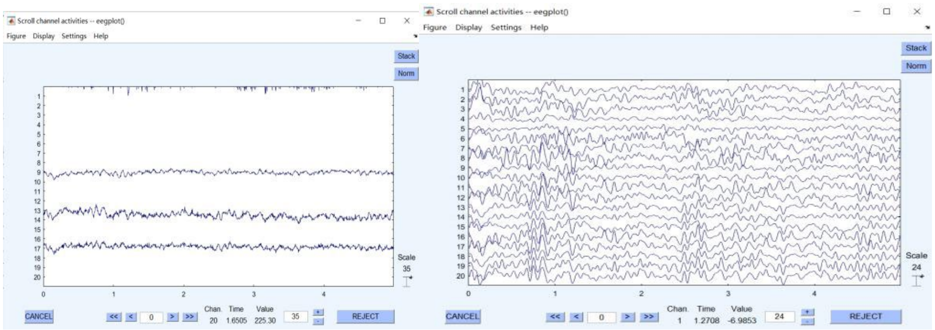

Figure 3: Signal display of char06 on 20 channels in S1_train_data before and after filteri

The effect of target recognition or classification prediction after data filtering is obviously much better than that of initial data analysis. Therefore, this article believe that the interference of EEG, ECG and other signals will affect the analysis of EEG signals, and filtering is a key step of data preprocessing.

When training the binary classification model, the ratio of positive samples to negative samples is 1: 5, that is, the number of positive and negative samples is unbalanced. If the unbalanced sample set is directly used for training and learning, the classifier can simply judge all samples as negative samples and achieve 83.33% accuracy, so it cannot achieve sufficient accuracy and recall rate on both positive and negative samples. For unbalanced data samples, we mainly balance the data set by resampling. First, we randomly sample the data, and then divide the data into training set and test set. By increasing the number of positive training samples and reducing the number of negative samples, the distribution of unbalanced samples becomes even, so as to improve the recognition rate of classifier for positive samples.The effect of target recognition or classification prediction after data filtering is obviously much better than that of initial data analysis. Therefore, this article believe that the interference of EEG, ECG and other signals will affect the analysis of EEG signals, and filtering is a key step of data preprocessing.When training the binary classification model, the ratio of positive samples to negative samples is 1: 5, that is, the number of positive and negative samples is unbalanced. If the unbalanced sample set is directly used for training and learning, the classifier can simply judge all samples as negative samples and achieve 83.33% accuracy, so it cannot achieve sufficient accuracy and recall rate on both positive and negative samples. For unbalanced data samples, we mainly balance the data set by resampling. First, we randomly sample the data, and then divide the data into training set and test set. By increasing the number of positive training samples and reducing the number of negative samples, the distribution of unbalanced samples becomes even, so as to improve the recognition rate of classifier for positive samples.

3. Model establishment and solution

In the process of model training, due to the high complexity of the model, it is easy to overfit (as shown in the figure below). As the model learns too many details from the noise data of the training set, the performance of the model on unknown data is not good. In terms of the operation results, the training error will be small and the test error will be large.L2 regularization refers to the sum of the squares of each element in the weight vector w and then the square root, usually expressed as w 2. The phenomenon of over-fitting of the pair of pins can be solved well by L2 regularization, mainly by adding constraints (prior knowledge) to minimize the empirical error function. When optimizing the error function, we tend to choose the direction of gradient reduction that satisfies the constraints, so that the final solution tends to be adjusted in accordance with the prior knowledge to eliminate the singularity. For S1 subjects, the fluctuation of training and test accuracy rate with the increasing number of iterations before and after regularization is shown in Figure 4, which verifies that "excessive learning details will blindly pursue the accuracy of training data and ignore the accuracy of test data".

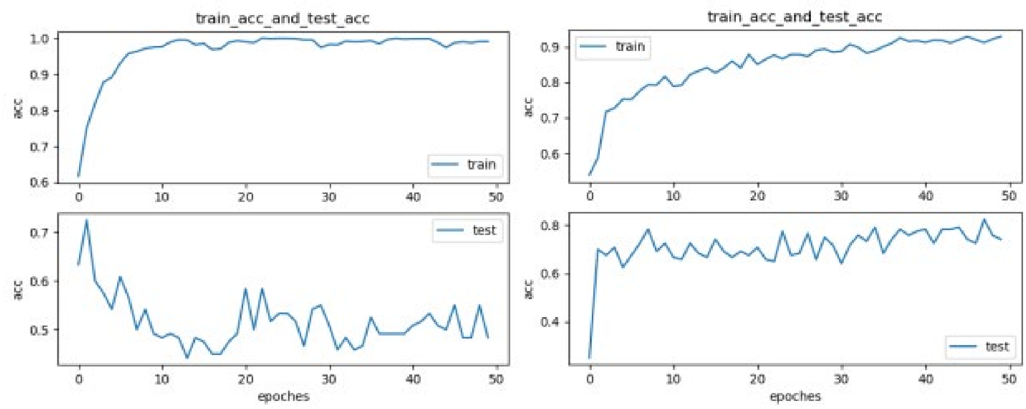

Figure 4: S1 recognition accuracy before and after regularization

About Convolutional neural Network (CNN), it is a deep learning model or multilayer perceptron similar to artificial neural network, which is commonly used to analyze visual images. Convolutional neural network is a kind of deep neural network with convolutional structure, which can reduce the amount of memory occupied by deep network. The three key operations of convolutional neural

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network are local receptive field, weight sharing and pooling layer, which effectively reduce the number of network parameters and alleviate the problem of model overfitting.

The topology structure of convolutional neural network is mainly composed of five layers, and the specific structure of each layer is shown in Table 1 below.

Table 1: Specific structure of each layer of convolutional neural network

Name of layer	Specific structure
Layer of input	Input initial sample signal (composed of 20 channels, each with 150 neurons)
Spatial feature convolution layer	A combination of 20 signal acquisition channels
Temporal feature convolution layer	A transformation and downsampling process in the time domain, set to half the sampling interval time
Fully connected layer	It is composed of one channel with 100 neurons. This layer is a fully connected layer, and the feature connections extracted from the previous channels are associated for comprehensive analysis
The output layer	One channel, two neurons, is used to represent the presence or absence of P300 signal

The whole convolutional neural network can be given in matrix form in the calculation process. Taking a single layer as an example, the number of rows and columns of the matrix calculated is different due to the different input and output dimensions and the number of neurons of each layer, but the overall calculation form is the same, and the parameters only need to be adjusted according to the specific situation of different layers. Assuming that layer i has m inputs, n neurons, and n outputs, the matrix of layer i is calculated as follows:

$$\mathrm{O}^{\mathrm{i}}=\begin{Bmatrix}\mathrm{O}^{\mathrm{i}}{}_{1}\\ .\\ .\\ .\\ \mathrm{O}^{\mathrm{i}}{}_{n}\end{Bmatrix}=f\left\{\begin{Bmatrix}w_{11}^{i}\dots w_{1m}^{i}\\ .\\ .\\ .\\ w_{n1}^{i}\dots w_{nm}^{i}\end{Bmatrix}\begin{Bmatrix}\mathrm{O}^{\mathrm{i-1}}\\ .\\ .\\ .\\ \mathrm{O}_{\mathrm{m}}^{\mathrm{i-1}}\end{Bmatrix}+\begin{Bmatrix}b_{1}^{i}\\ .\\ .\\ .\\ \mathrm{b}_{\mathrm{n}}^{\mathrm{i}}\end{Bmatrix}\right\} \tag{1}$$

O^i represents the output vector of layer i, n represents the number of neurons of layer i, the m-dimensional output vector of layer i-1 becomes the input vector of layer i, the first n× m matrix in the brackets represents the weight coefficient matrix, that is, n neurons, and each neuron has m weight coefficients. The weight coefficient matrix is multiplied by the input vector to obtain an n-dimensional vector, and the last item in the brackets is the n-dimensional bias vector. After adding the two vectors, the activation function f is operated, and the output vector of the ith layer is finally obtained.

Random forest (RF) is to build a forest in a random way. There are many decision trees in the forest (the number of decision trees depends on the initial setting of human beings). Different decision trees are independent of each other and do not interfere with each other in the calculation process, which reflects the integration idea of random forest algorithm. The "random" of random forest has two meanings, namely, the randomness of sample sampling and the randomness of feature sampling. After the forest is obtained, when a new input sample needs to be analyzed, each decision tree in the forest performs an operation judgment separately to determine which class the input sample should be classified into. Finally, the conclusions of all decision trees are integrated to find out the most selected classes, so as to classify the sample into which class. In addition to classification prediction, random forest can also be used for regression. The basic idea of the algorithm for classification prediction can be simplified as shown in Figure 5 below:

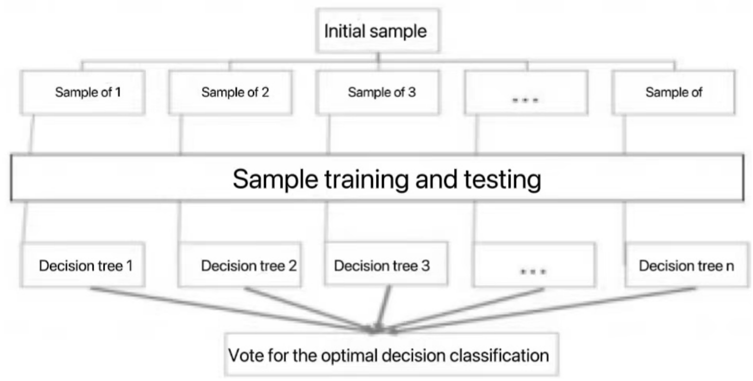

Figure 5: Simplified analysis of random forest

The random forest algorithm mainly includes three parts in the process of implementation: input, algorithm and output, and the final classification or regression results are obtained after a series of transformations. The specific process is shown in Table 2 below:

Table 2: Random forest implementation flow chart

Random forest process	Concrete implementation
Input in	Sample set D = {(x1, y), (x2, y2),... (xm,y m)} Number of weak classification iterations T (number of decision trees)
Algorithm of	For t=1,2,... For T trees: 1. Select m training samples from the training set randomly and with replacement as the training sample set Dt of the decision tree 2. Train the TTH decision tree model by randomly selecting a subset of features from Dt 3 Each decision tree is unpruned and grows until the specified tree depth If it is a classification prediction, the category or one of the categories with the most votes cast by T decision trees shall be the final category; In the case of regression analysis, the value obtained by arithmetic average of the regression results obtained by T decision trees is the final model output
Output of goods	The final strong classification or strong regression results

The letter to be recognized can be obtained by querying the serial number of the row and column in the letter matrix where the letter is located. Therefore, the problem of identifying the word motif is transformed into the problem of identifying the location of P300 signal from six rows and six columns. We judged whether the P300 signal appeared in the current cycle in each round of 12 blink cycles. In this way, we transformed the letter recognition problem into a discrimination problem of whether the signal appeared.

The 1-20Hz training data X and test data C obtained after filtering were used to segment the data according to the flashing period of each letter. The data segment with P300 signal in the training set was marked as 1, and the rest of the data segment was marked as 0. The training data were processed out of order and multiplication according to the above preprocessing process. The training data X is further divided into training set A and test set B, and the letter label of test set is hidden.

For the data of training set A, since the total time from stimulus occurrence to the end of P300 signal is 600ms, and the sampling time interval is 4ms, a signal to be discriminated has 150 data and 20 channels. If the signal contains P300 signal, its label is set to 1; otherwise, it is 0. In this way, we adopt the form [(150X20),(0 or 1)] as the source of learning.

In this problem, we respectively use support vector machine (SVM), random forest (RT), convolutional neural network (CNN) three methods to perform the discrimination function. Due to the small amount of data mastered, the common allocation ratio of training set and test set is 70% data set for training set and 30% data set for test set. However, due to the small amount of data, we use the allocation ratio of 80% training set and 20% test set.

For SVM and random forest, the row and column where the signal is located are directly judged. The input form for both SVM and random forest is [3000,(0 or 1)], that is, the first two velas of [(150X20),(0 or 1)] are straight. The parameters of the SVM algorithm are set as follows: the penalty

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coefficient C=1, the kernel function is the Gaussian kernel function, and the kernel parameter gamma=2; The parameters of the random forest are set as follows: the number of trees is 400, the depth of trees is 60, and the cross-entropy criterion is used.

For the convolutional neural network, because the convolutional neural network module encapsulated by TensorFlow is used, the value of the input (150X20) matrix of [(150X20),(0 or 1)] is listed separately as one-dimensional, so the input is four-dimensional data that satisfies the convolutional neural network module.We use data from all five rounds for the forecast.The discrimination effect of each algorithm is tested on test set B, and the vertical comparison shows that the use effect of convolutional neural network is significantly stronger than that of support vector machine and random forest. Meanwhile, the horizontal comparison shows that the discrimination accuracy of convolutional neural network for S1 is weaker than that of S2 to S5, which we guess may be related to individual differences between people. The consistency of S1's brain signal output was worse than that of others. Therefore, we further averaged the five rounds of signals of S1 and obtained one round of relatively stable signals. The convolutional neural network was used for scoring and judgment again. The results on test set B showed that the prediction success rate was improved but not high, which may be due to the fact that only one round of data set remained after averaging, and the training set was too small. After training the algorithm for 10 times and testing the average, the results are shown in Table 3 below:

Table 3: Comparison of recognition accuracy of three different algorithms under round-by-round analysis or summary analysis

Algorithm of	S1		S2	S3	S4	S5
CNN	S1 before averaging	So S1 is averaged	79.0%	79.1%	86.7%	84.9%
	70.2%	80.6%				
SVM	52.7%		54.4%	60.0%	59.8%	62.4%
RT	53.3%		57.6%	63.3%	60.0%	64.7%

Among the three algorithms, convolutional neural network algorithm has the highest prediction success rate, so convolutional neural network is used in the next prediction process of prediction data set C, as shown in Table 4.

Table 4: Multiple results of convolutional neural network algorithm for identifying target accuracy

Round of rounds	S1 before averaging	S1 before averaging	S2	S3	S4	S5
1	MFG2CNB4A0	ML52CTKXAX	MF52ITKXA	ML52ITKXA	MF52ITKXB0	MF52ITKXA0
2	ML52CBK4AR	ML52CTK4GR	MF52ITK4A	MF52ITKXA	MF52ITKXB0	MF52ITKLA0
3	MF58CNEXA0	ML58CNKXAX	MF52ITK45	MLM2ITKXA	MF52ITKXA	MF52ITKXA0

Since the prediction results of S1 are still quite different from those of the other four groups, and the prediction accuracy of S1 by the aforementioned three algorithms is relatively low (we assume that the test behavior of the subject has certain abnormalities), the prediction results of S1 are discarded. According to the prediction results from S2 to S5, the letter with the highest frequency in each position is shown in Table 5 below:

Table 5: Possible values and frequencies of 10 targets to be identified

Location	1	2	3	4	5	6	7	8	9	10
Letter of letters	M	F	5	2	I	T	K	X	A	0
Frequency of frequency	12	10	11	12	12	12	12	9	9	6

Since the prediction result of S1 is abandoned, and S2 and S3 have no prediction demand of the 10th letter, the upper limit of the total frequency of the first nine letters is 12, and the upper limit of the total frequency of the 10th letter is 6. As can be seen from the above table, the consistency of the forecasts is very high. Therefore, for the 10 targets to be identified, we predict the result as MF52ITKXA0.

4. Conclusion

In this study, the advantages and limitations of CNN model in processing EEG signal recognition are deeply explored by comparing the performance of convolutional neural network (CNN) with traditional methods in brain-computer interface (BCI) recognition task. The following are the main conclusions of this study: Firstly, this paper verifies the effectiveness of CNN in processing EEG signals. Compared with traditional support vector machine (SVM) and random forest (RF) methods, CNN shows higher recognition accuracy and stability in multiple rounds of tests. Especially in the case of large individual differences, CNN can better capture complex spatial and temporal features and improve the accuracy of recognition. Secondly, although CNN shows significant advantages in performance, its model complexity and training cost are correspondingly high. In practical applications, the balance between recognition accuracy and computing resources needs to be weighed to ensure the real-time and reliability of the system. Finally, this study shows the optimization strategies for CNN model, including adjusting network structure, optimizing hyperparameters and adding data enhancement techniques, which play a positive role in improving recognition performance. Future research can further explore more complex CNN architectures and more refined data preprocessing methods to further improve the overall performance of brain-computer interface systems.

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