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1	Deep Learning for Classification of Sleep EEG Data during the
2	Epidemic of Coronavirus Disease
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7 Abstract

⁸ Sleep is an important part of the body's recuperation and energy accumulation, and the

⁹ quality of sleep also has a significant impact on people's physical and mental state during the

¹⁰ epidemic of Coronavirus Disease. It has attracted increasing attention on how to improve the

¹¹ quality of sleep and reduce the impact of sleep-related diseases on health during the Epidemic

¹² of Coronavirus Disease. The electroencephalogram (EEG) signals collected during sleep

¹³ belong to spontaneous EEG signals. Spontaneous sleep EEG signals can reflect the body's

¹⁴ changes, which is also an basis for diagnosis and treatment of related diseases. Therefore, the

¹⁵ establishment of an effective model for classifying sleep EEG signals is an important auxiliary

¹⁶ tool for evaluating sleep quality, diagnosing and treating sleep-related diseases.

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18 Index terms— Sleep EEG; deep learning; softmax function; adam algorithm; multiple classifications 19 problem.

In this paper, outliers of each kind of original data were detected and deleted by using the principle of 3 Sigma and k-means clustering + Euclidean distance detection method. Then, using the Adam algorithm with

adaptive learning rate constructs the Softmax multi-classification BP neural network the model, and relatively
 high accuracy and AUC values were finally obtained during the Epidemic of Coronavirus Disease.

24 1 Introduction

he sleep process is a complex process of dynamic changes. According to R&K, the international standard for the interpretation of sleep stages, there are different states during sleep.

In addition to the awake period, the sleep cycle consists of two alternate sleep states, namely rapid eye movement(REM), and non-REM.

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³⁰ 2 Overview of BP Neural Network

An artificial neural network gets widely used in some aspects, including pattern recognition, function approximation, data compression, data classification, data prediction, etc. [1][2][3][4][5][6] BP neural the network is an algorithm in ANN. Figure ?? shows the basic structure of the BP neural network. 1 + ? t t () 1 ? ? ? t t f g ?

³⁴ ? Computing the gradient. () t t t g m m ? ? + ? ? ? 1 1 1 1 ? ? Update biased first moment estimate. () 2

35 2 1 2 1 t t t g v v ? ? + ? ? ? ? ?

Where ? is the step length, In this paper, the whole training process of the improved BP neural network model is:

Step 1: Parameter initialization. Determine the node number of the network input layer, hidden layer and output layer, and initialize the weight, bias between each layer, then initialize learning rate.

Upgrade biased second moment estimate. ??)t t t v v 2 1 ?? ? ? Compute bias-corrected second draw moment estimate. ? ? ? ? + ? ? t t t t v m ?- 1 - Upgrade parameters.

42 Step 2: Calculate the output of the hidden layer. The hidden layer output is calculated by the weight and 43 bias between the input vector and the connection layer and the ReLU activation function.

Step 3: Calculate the output of the output layer. through the hidden layer output and connection weights and bias and the Softmax activation function calculate the predicted output.

46 Step 4: Calculate Softmax cross-entropy as cost function according to predicted output and real label.

47 Step 5: Back propagation, and this paper use the adaptive learning rate Adam algorithm [7] to update the 48 weight and bias.

49 Step 6: Determine whether the cost reaches the error range or the number of iterations. If not, return step 2.

⁵⁰ 3 III. Data Description and Preprocessing

Data were collected from 3000 sleep EEG samples and their labels are taken from different healthy adults during 51 overnight sleep. The first is a "known label," which represents the different sleep stages in digital form: stage 52 wake (6), rapid eye movement (5), sleep I (4), sleep II (3), and deep sleep (2); The second to fifth columns are 53 the characteristic parameters calculated from the original time sequence, successively including "Alpha", "Beta", 54 "Theta" and "Delta", which correspond to the energy proportion of EEG signals in the frequency range of "8-55 13Hz", "14-25Hz", "4-7Hz" and "0.5-4Hz" respectively. The unit of characteristic parameters is the percentage. 56 This paper gives raw data stage wake (??), and REM. (??), sleep I (4), sleep II (3), deep sleep (2), four brain 57 electrical signal energy proportion of five sleep stages of brain electrical signal energy proportion, but the original 58 data are generally given there are some abnormal data outliers or missing value, therefore we to each index of 59

60 the five sets of data make a boxplot graph, the result is as follows in figure 4. Five sleep period by Figure 4

shows, there are some outliers, namely, these all belong to the original data of abnormal points, this paper uses

the principle of 3 sigmas [8] will each table of data deletion, then after the processing of five tables to merge, and then using the K-means clustering + Euclidean distance outlier test [9], to find and remove outliers, as shown

then using the K-means clustering + Euclidean distance
in figure 5, a total of 2883 samples after pretreatment.

⁶⁵ 4 IV. Model Training and Prediction

We divided the data into a training set and test set in a ratio of 2:8. We trained and tested the data using the traditional decision tree model [10] (DT) and support vector machine model (SVM), and compared the classification effect with the accuracy rate and AUC value as evaluation indexes. The results are as follows: As can be seen from Table 1, the accuracy of Adam-BPNNet in several traditional methods is relatively high. Figure 6 shows the ROC curve of each classification method. The prediction result is the best classification effect obtained after many experiments. In the early stage of experiment, the classification accuracy is low. After repeated debugging of the number of hidden layers and nodes, the best AUC value of this experiment is 0.83.

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74 5 Conclusion

This study is mainly based on theoretical research and combines theory with practice. This paper uses BP neural 75 network based on an adaptive learning rate Adam algorithm for data classification. Also, this paper selects 76 Softmax as the activation function in the output layer, enabling the model to have good selflearning and self-77 adaptive ability. The most important thing is that the network has good generalization ability. When designing 78 79 the classifier, it should consider whether the network can correctly classify the objects it needs to classify, and whether the network can correctly classify the unseen or noise-polluted patterns after training. The classification 80 AUC value of this study is 0.83, which is scientific to a certain extent and can be used as auxiliary tool for the 81 evaluation of sleep quality, diagnosis and treatment of sleep-related diseases. 82

6 Conflict of Interest

We have no conflict of interests to disclose and the manuscript has been read and approved by all named authors.



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Figure 3: Figure 1



Figure 4: Figure 1



Figure 5: Figure 1 :



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Figure 6: Figure 2 : Figure 3







Figure 8:



Figure 9:



Figure 10:



Figure 11: Figure 4 :



Figure 12: Figure 5 :



Figure 13:



Figure 14: Figure 6 :

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Classifier	Accuracy rate
DT	0.59
SVM	0.68
Adam-BPNNet	0.73

Figure 15: Table 1 :

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Classifier	AUC
DT	0.77
SVM	0.80
Adam-Bennett	0.83
Table 2 shows that in the Adam-BPNNet model,	
fewer training sets will still have a better classification	
effect.	

Figure 16: Table 2 :

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