Hindawi
Scientific Programming
Volume 2022, Article ID 6048088, 9 pages
https://doi.org/10.1155/2022/6048088

Research Article

Identification and Modeling of College Students' Psychological Stress Indicators for Deep Learning

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Received 8 November 2021; Revised 29 November 2021; Accepted 9 December 2021; Published 11 January 2022

Academic Editor: Baiyuan Ding

Aiming at the problems of low accuracy of recognition results, long recognition time, and easy interference in traditional methods, a deep learning-oriented recognition modeling method of college students' psychological stress indicators is proposed. First, the ECG signal is collected by the ECG signal acquisition system, and the wavelet transform method is used to denoise the collected ECG signal. Then, the sequential backward selection algorithm is used to select the features of psychological stress indicators to reduce the feature dimension. Finally, based on the convolutional neural network in deep learning technology, a mental pressure indicator recognition model is established and the model parameters are optimized to realize the recognition of college students' mental pressure indicators. Experimental results show that the method in this paper has high recognition accuracy, has high recognition efficiency, is not susceptible to interference, and has certain feasibility and effectiveness.

1. Introduction

People in modern society are exposed to various pressures, and often need to bear pressures from work, life, economy, interpersonal relations, and so on [1, 2]. Continuous stress will bring psychological and physiological obstacles and defects. Tracking and recording individual's daily psychological stress state in real time, timely warning in case of abnormalities, and giving appropriate intervention and guidance can well help individuals maintain a good psychological state [3, 4]. For a long time, people have used interviews, psychological questionnaires, and other methods to monitor their psychological stress status. This method often requires the participation of psychologists. Real-time monitoring is not possible, and it is more difficult to extend to a large number of people under pressure. At present, there are no mature indicators and methods recognized in the industry that can accurately assess the level of psychological stress. Therefore, it is very important to design a method that can accurately identify indicators of psychological stress [5].

In recent years, the use of noninvasive sensors to collect physiological indicators and identify psychological stress has become a major research hotspot. These studies aim to collect relevant physiological indicators and identify psychological stress indicators by wearing sensors that do not affect their daily activities. With the help of wearable devices, users can collect relevant physiological indicators anytime and anywhere and upload data to the service platform via the mobile Internet. The service platform uses the data received to evaluate the psychological stress level of users and, under the guidance of experts, provides users with effective intervention and guidance through the mobile Internet. This is a typical mode of psychological stress tracking services for mobile health [6, 7]. In addition, a pressure identification algorithm based on improved particle swarm optimization BP neural network is proposed in reference [8]. Based on the basic particle swarm optimization model, the shrinkage factor is introduced. Under the action of the shrinkage factor, the boundary limit of speed disappears, and appropriate parameters are selected to ensure the boundedness and convergence of the PSO algorithm, so as to realize the optimization of BP neural network. The stress was induced by mental arithmetic task, the ECG signals under high and low pressure were collected, the eigenvalues of heart rate variability related to psychological stress were extracted, and the characteristic data were compared and analyzed. The classification model of psychological stress degree is established, and the BP neural network is optimized by the improved PSO model to identify psychological stress. The results show that the recognition rate of psychological stress can reach 94.83%, and the recognition effect is good. Reference [9] proposes a psychological index recognition modeling method based on social media data, summarizes its feasibility in psychological measurement, introduces feature extraction methods, common machine learning algorithms, and application scenarios, and summarizes and respects the advantages and disadvantages of psychological index recognition modeling. This measurement method is based on social media data and has unique advantages compared to the self-report method, such as high timeliness, retrospective measurement, and good ecological validity. However, the method of identifying and modeling mental indicators based on social media also has limitations in terms of learning costs and hardware costs. In the future, researchers need to further explore the association mechanism between social media information and user psychological variables and combine the psychological indicator recognition model with traditional psychological research methods for more exploration and application.

Although the above methods can realize the identification of psychological stress indicators to a certain extent, there are problems of low recognition accuracy, susceptibility to interference, and long recognition time. It can be seen that it is necessary to conduct research in this area. In this context, this article takes college students as the research object and proposes a deep learning-oriented method for identifying and modeling the psychological stress indicators of college students, aiming to improve the effect of identifying psychological stress indicators. Before establishing the model, the ECG signal after the change of college students' psychological pressure is collected by the heart electrical signal acquisition system and the collected ECG signal is preprocessed by the wavelet transform algorithm. So far, the ECG signal preprocessing is realized. After preprocessing, the sequential backward selection algorithm is used to select the characteristics of psychological stress indicators. Finally, the convolution neural network in deep learning technology is used to establish the identification model of college students' psychological stress indicators.

2. Preprocessing of Psychological Stress Indicators for College Students

2.1. ECG Signal Acquisition and Processing

2.1.1. ECG Signal Acquisition. The acquisition and processing of ECG signals are the prerequisite for the identification of psychological stress indicators. When collecting data, the design of the pressure induction scheme and the different pressure states of the collection require scientific selection and judgment. In order to accurately analyze the psychological stress indicators of college students and extract features, it is necessary to process the interference noise in the collected original ECG signals [10, 11].

The ECG lead system of the ECG signal acquisition system selects the I lead system, and the acquisition block diagram is shown in Figure 1. Among them, the lead electrodes RA and RL are respectively connected to the right upper limb and right lower limb, and LA is connected to the left upper limb; the left and right upper limb ECG signals pass through the predifferential amplifier circuit and the main amplifier circuit, band-pass filter circuit, and power frequency trap circuit; the right lower limb is connected to the right leg drive circuit, also through the predifferential amplifier circuit, and finally output from the output of the power frequency trap circuit, and the output signal is connected to the AIO port in NI My RIO to achieve ECG data acquisition [12, 13].

For the study of psychological stress identification methods, the correctness and validity of data are the key to subsequent processing and analysis. Therefore, the collection of ECG signals is the basis for identifying psychological stress. This article builds the circuit according to the block diagram of the ECG acquisition module shown in Figure 1. Then, on this basis, the NI My RIO embedded development platform is used as the acquisition card, and the FPGA technology in NI My RIO is used to control the acquisition card to collect the ECG signals. Connect the output of the acquisition circuit to the analog input of NI My RIO. Finally, use the LabVIEW FPGA module to design the acquisition program and store the collected original ECG data through the FIFO (First Input First Output) memory in the FPGA. The ECG data stored in FIFO memory are finally implemented by the RT terminal programs read and display.

2.1.2. ECG Signal Preprocessing. Due to the characteristics of the ECG signal itself and the influence of the equipment, the original ECG signal collected above often contains a lot of noise. These noises mainly include the noise generated by the equipment itself, respiratory wave noise, and myoelectric interference. These noises will cause changes in the ECG signal waveform to varying degrees, including amplitude changes, baseline drift, and so on. Therefore, these noises must be filtered out before further analysis of the ECG signal [14].

As a signal analysis tool developed in recent years, wavelet transform has its characteristics including orthogonality, direction selectivity, small amount of analysis data, and resolution variability. These characteristics of wavelet transform make it often used for noise filtering and waveform detection of ECG signals [15, 16].

The basic wavelet definition is as follows: suppose $F(t) \in S^2(t)$ represents a square integrable real number space, its Fourier transform is $F(k)$, and $F(k)$ satisfies the allowable condition:

$$A_F = \sqrt{\frac{|F(k)|^2}{|k|}}. \tag{1}$$

Here, $F(k)$ represents a basic wavelet. The wavelet generated by the basic wavelet is

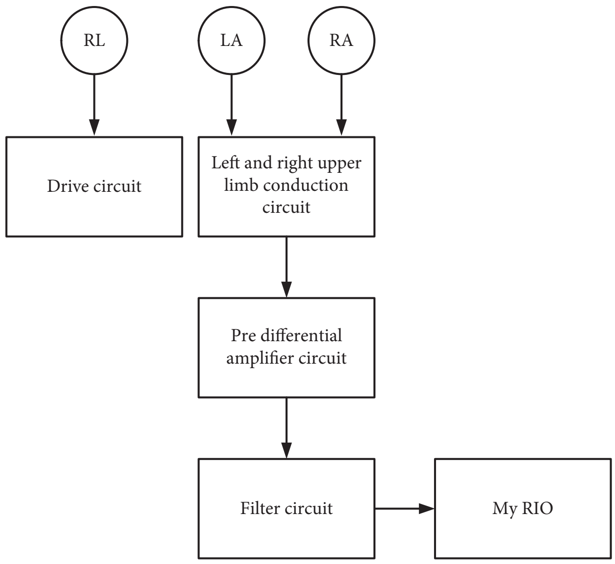

FIGURE 1: Working principle diagram of the ECG signal acquisition system.

$$F_{ij}(n) = F\left(\frac{n-j}{i}\right) \times A_F. \tag{2}$$

For a continuous signal $F(t) \in S^2(t)$ (a space with limited energy), the continuous wavelet transform (CWT) of $F(t)$ is

$$S(a,b) = \frac{R(a,b)\sum_{k=1}^{n} a_k b_k}{\sqrt{\left(\sum_{k=1}^{n} a_k^2\right)\left(\sum_{k=1}^{n} b_k^2\right) \times F(t)}}. \tag{3}$$

Here, a_k represents the scale factor; b_k represents the delay factor; and $R(a,b)$ represents the continuous wavelet basis function.

In actual ECG signal analysis, discrete wavelet transform (DWT) is generally used to analyze the signal. Discrete wavelet transform generally uses binary transform to calculate the time and scale wavelet coefficients of discrete intervals; that is to say, the choice of scale and time is usually carried out in the exponential way of 2 [17, 18]. The discrete wavelet transform of any function $F(t)$ is

$$W(a,b) = \int_t F_{ij}(a,b) \times F_{ij}(t)\mathrm{d}t. \tag{4}$$

Here, $F_{ij}(t)$ represents the shrinkage threshold function, and its calculation formula is as follows:

$$F_{ij}(t) = V_i^S(j) + (1-\alpha)\mathrm{Re}_{ij}. \tag{5}$$

The two key factors for processing the ECG signal by wavelet transform are the choice of wavelet base and the determination of the number of decomposition layers. Commonly used wavelet bases include Haar wavelet, Daubechies (dbN) wavelet, Mexican Hat (mexh) wavelet, Morlet wavelet, and Symlets wavelet. This article uses the wavedec function of the Matlab analysis software to select the db5 wavelet to decompose the ECG signal in three layers, and on this basis, the wdencmp function is used to achieve the denoising of the original signal. The denoising effect of the original ECG signal is shown in Figure 2. Figure 2(a) is the original ECG signal of a certain subject collected, and Figure 2(b) is the ECG signal after wavelet denoising.

2.2. Feature Selection of Psychological Stress Indicators. According to the ECG signal denoising results obtained in Section 2.1, further select the characteristics of psychological stress indicators. When classifying numerous ECG signal features through the classifier, not every feature is useful, and this part of the feature is considered to be original features [19]. In the field of deep learning, the dimension of the feature space sent into the classifier should not be too high; otherwise, it will cause the so-called "dimension disaster," make the classifier model complex, and reduce the generalization ability [20–22]. Therefore, it is necessary to select the features with less correlation between features from the original feature set as the feature set. The essence of feature selection is to search the optimal or suboptimal subset and select the features with the highest classification contribution to the data set as the feature subset. In this paper, sequential backward selection (SBS) is selected as the feature selection algorithm.

Backward selection is a bottom-up feature selection algorithm. Its core idea is to take the complete set of features to be selected as the initial feature set, delete a feature with the least contribution to classification each time, and gradually eliminate and judge it. If the dimension of the feature decreases to 1, it will stop [23, 24]. The algorithm flow of the backward selection algorithm mainly includes the following processes:

Step 1. Take all the features as the initial $Q_0 = P$.

Step 2. Remove a feature from the feature set, so that the removed feature set Q_g is optimal, namely,

$$\overline{P} = \operatorname{argmax}\left[D\left(Q_g - x\right)\right]. \tag{6}$$

Here, $\overline{P}$ represents removing the feature from the feature set; the minus sign is not a subtraction operation for feature values in the usual sense.

Step 3. Update the feature set so that

$$Q_{g+1} = \sum_{i,j=1}^{M} E\left[W_{ij}(t)\right]. \tag{7}$$

Here, E represents the frequency domain index of the psychological stress index feature and $W_{ij}(t)$ represents the single time domain of the psychological stress index feature.

Step 4. Return to the second step until the feature dimension drops to 1.

According to the above steps, redundant features are eliminated, the accurate selection of psychological stress index characteristics is realized, and the data basis for the identification of the psychological stress index of college students is provided.

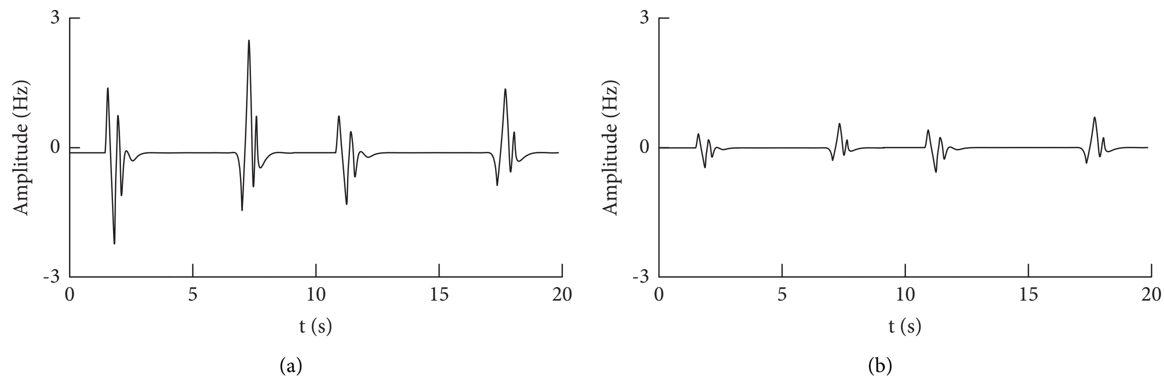

Figure 2: ECG signal comparison before and after denoising. (a) Original ECG signal. (b) ECG signal after denoising.

3. Recognition and Modeling Method of Psychological Pressure Indicators for College Students Oriented to Deep Learning

The identification of psychological stress indicators can be used as the basis for psychological doctors to assist in diagnosis, help psychological doctors treat psychological patients more effectively, and enable people to understand their own stress, reduce pressure in time, and relieve daily stress according to the understanding. In addition, it can also help the school to understand the physical and psychological state of college students for effective management. It can also enable the government to correctly count the general psychological pressure of college students, so as to take some measures to improve social medical care. Therefore, based on ECG signal acquisition and processing and psychological stress index feature selection, this paper uses deep learning technology to accurately identify college students' psychological stress index.

3.1. CNN Model Construction. Deep learning technology subverts the development rules of traditional artificial intelligence systems, enabling computers to simulate the operation mode of the brain and learn and recognize abstract patterns through multilayer convolution neural networks, so as to solve some general pattern recognition problems [25–27], which means that any task involving a large amount of data may benefit from deep learning. Based on the idea of deep learning, this paper puts forward a technical idea of target recognition of college students' psychological stress indicators [28, 29].

Convolutional neural network CNN is a deep learning model that can effectively extract targets. Therefore, CNN is used to identify the psychological stress indicators of college students and establish a CNN model [30]. The CNN model is generally composed of an input layer, a convolutional layer, a subsampling layer, a fully connected layer, and an output layer. The feature extraction work of convolutional neural network is mainly realized by convolutional layer and subsampling layer [31, 32]. In the convolutional layer, a feature plane is composed of the arrangement of neurons, and the weight matrix shared by all neurons in a feature plane is also called a convolution kernel. The feature surface of the upper layer can be output feature surface through convolution and activation function. In traditional neural networks, sigmoid is often used as the activation function, but sigmoid is easy to cause saturation during the gradient descent process, thereby terminating the gradient transfer [33]. The ReLU function has the advantages of fast convergence speed and simple gradient solution. Therefore, the ReLU function is commonly used as the activation function in CNN at present, and the calculation formula is as follows:

$$U(x) = \sum_{i=1}^{M} D_i(w) w_k. \tag{8}$$

Here, $D_i(w)$ represents the radial basis function and w_k represents the neuron.

The convolutional layer gradually extracts different features through the process of convolution. The higher the number of layers, the more advanced and abstract the extracted features.

The subsampling layer is also called the pooling layer, in which the feature surfaces correspond to the feature surfaces in the convolutional layer, and the number is the same. The pooling layer further extracts the output features of the convolutional layer, which can effectively reduce the feature dimension. Commonly used pooling methods include random pooling, average pooling, and maximum pooling. The fully connected layer can summarize the local features extracted by the convolutional layer and the sampling layer and finally enter the classifier for classification [34]. CNN uses the loss function to measure the robustness of the model. It can estimate the difference between the predicted value and the true value in the model. The smaller the value, the better the robustness of the model. Most models use the mean square error as the loss function, and its calculation formula is as follows:

$$E_j^2 = \left| \frac{\max\left(b_{1j}, \ldots, b_{nj}\right) + \min\left(b_{1j}, \ldots, b_{nj}\right)}{2} - \partial_j \right|. \tag{9}$$

Here, b_{ij} represents the supervision information of the mean square error loss and ∂_j represents the cross entropy.

The deep features extracted by CNN contain high-level semantic information and maintain certain invariance to zoom, translation, and so on, which significantly reduces the gap between high-level semantics and low-level features [35]. The multilayer convolutional neural network structure used in this article includes an input layer, a three-layer convolutional layer, a three-layer sampling layer, a fully connected layer, and an output layer. The size of the convolution kernel is 5×5, and the information of the fully connected layer is extracted as the global feature, that is, the psychological pressure index feature of college students.

3.2. Model Parameter Optimization. For the designed CNN model, it is very important to optimize each node into the best state. This requires a large amount of training in combination with the training samples. Each training is a correction iteration of the whole network parameters, so that the constructed network can conduct a recognition learning on the concerned goals, until the goal cognition learning under various states of the training samples forms a representative description of the concerned goals. The better the network model is optimized, the deeper the learning of the target is, and the more transparent the description is, the higher the accuracy of the model is for detection [36]. Therefore, model parameter optimization is very important.

Suppose there is a fixed training set:

$$C = \left\{ \left(c^1, v^1\right), \left(c^2, v^2\right), \ldots, \left(c^m, v^m\right) \right\}. \tag{10}$$

Here, m represents the number of training samples. The batch gradient descent algorithm can be used to train the convolutional neural network. Specifically, for a single training sample (c, v), the cost function can be defined as

$$\mu(W, b; c, v) = \sqrt{\sum_{i,j=1}^{m} \left(Y_{ij} - E_{ij}(Q_i)\right)^2}. \tag{11}$$

Here, Y_{ij} represents the location of the optimized region of the convolutional neural network; Q_i represents the network parameters; and E_{ij} represents the classification probability.

The cost function c is the cost function of a single sample after the conversion between W and b, and then the cost function for m training samples can be defined as

$$\mu(W, b) = \frac{\sum_{i=1}^{m} Y'_{ij} w_j}{\sum_{i=1}^{m} \sigma(Q_m)}. \tag{12}$$

Here, Y'_{ij} represents the output value distribution of each neuron in the convolutional layer in response to different inputs and $\sigma(Q_m)$ represents the cost function of the feedforward neural network.

The first term $\mu(W, b)$ of the cost function is the average of the sum of squared differences. The second item is an adjustment item (also called the weight decay item). The purpose is to reduce the magnitude of the weight and prevent overfitting. Assuming that H_l represents the number of neurons in layer l and H_{l+1} represents the number of neurons in layer $l+1$, the sum of the square weights between each neuron in layer l and all neurons in layer $l+1$ is G, and its calculation formula is

$$B_{ij}^{l} = \frac{\sum_{i=1}^{l} \sum_{j=1}^{l+1} \left(H_{ij}^{l}\right)^2}{\left(R_r / G_r\right)^2}. \tag{13}$$

Here, R_r represents the weight connection value between neurons and G_r represents the mean value of the corrected distance between neurons.

In each iteration of the gradient descent method, the parameters W and b are updated according to the following formula:

$$\begin{aligned} W_{ij}^{l} &= I_{ij}^{2} \times \mu(W, b), \\ b_{ij}^{l} &= \psi_{ij}^{2} \times \mu(W, b). \end{aligned} \tag{14}$$

Among them b_{ij}^{2} represents the output information of neurons; ψ_{ij}^{2} represents the amount of information transferred between networks.

Finally, the iterative steps of the gradient descent method are repeated to reduce the value of the cost function $\mu(W, b)$, and then the optimal parameters of the CNN model are solved.

3.3. Realization of the Recognition of Psychological Pressure Indicators for College Students. Based on the CNN model constructed in Section 3.1 and the obtained model parameter optimization results, the psychological pressure indicators of college students are identified. The following is a specific analysis of the process of identifying the psychological pressure indicators of college students.

First, they need to obtain the self-report score of college students' psychological characteristics. At present, most of the self-report scores used in the research are self-assessment scale scores. The number of users using social media data for psychological modeling is generally large. For example, the number of users in the research on Facebook application MyPersonality is generally more than 1000, up to 390,000 users. Therefore, in this paper, the psychological characteristics of college students are processed in the form of quantitative coding, that is, the step of feature extraction. Commonly used coding methods include classification, frequency, frequency, building sparse matrix, and so on. Based on the selection results of psychological stress index features obtained in Section 2.2, this paper further obtains the psychological stress index features of college students by establishing a sparse matrix. The sparse matrix is

$$\psi_{(W,b)} = \frac{\omega_s \lambda_m}{\sqrt{\left(R_r / s\right)^2 + \left(\omega_s\right)^2}}. \tag{15}$$

Here, ω_s represents the sparse coefficient of the sample to be identified and λ_m represents an over-complete dictionary.

Second, select appropriate deep learning methods to establish a mapping relationship between the user's self-report score and the corresponding psychological stress index characteristics, and use cross-check to verify the calculation effect of the model. Cross-checking is the most commonly used model performance evaluation method in the deep learning modeling process. The specific operation is to divide the data set into a training set and a test set, and use the training set to model and evaluate the model performance with the test set. The data set will be divided multiple times until each data set has been done on the training set and also on the test set. Cross-validation can make full use of the original data and avoid the impact of unbalanced random partitioning on model performance, and at the same time, it can also try to avoid overfitting of the model.

Finally, a feature recognition model for college students' psychological stress indicators is obtained. When data related to college students' psychological stress are input, feature extraction, model calculations, and output of the user's psychological feature values can be automatically performed according to the characteristics of the model, and the results of psychological stress indicator recognition can be obtained.

In summary, the general process of identifying and modeling college students' psychological stress indicators includes several main parts such as ECG signal acquisition and processing, feature selection and extraction, modeling and parameter optimization, and result output. The specific process of identifying and modeling college students' psychological stress indicators is shown in Figure 3.

4. Experimental Verification Research

In order to verify the validity and application value of the proposed deep learning-oriented college students' psychological stress index identification modeling method, experimental verification is carried out. In the experiment, the pressure recognition algorithm based on the improved particle swarm optimization BP neural network (method in reference [8]) and the psychological indicator recognition modeling method based on social media data (method in reference [9]) are used as comparison methods. The application effects of different methods are compared and experimental conclusions are drawn.

4.1. Experiment Preparation. Participants in this experiment are undergraduates and graduate students (between 19 and 25 years old) of a certain university. The participants are required to have no mental illnesses and be able to follow the guidance of the experimenters and cooperate to complete the experiment. To ensure the universality of the experiment, testers include engineering students and liberal arts students. There are 60 subjects in this experiment, including 36 males and 24 females. The distribution of test subjects is shown in Table 1.

In order to more effectively evaluate the recognition effects of different methods, in the experiment, the tester's calm state is regarded as a low pressure state, and this part of the mental arithmetic task process is regarded as a high pressure state. During the mental arithmetic task test, 20 mental arithmetic questions will be tested to induce the tester's psychological stress state. At the same time, in order to ensure the effectiveness of the tester's stress state, the time will be set for the questions in the mental arithmetic task during the experiment, and the subjects are required to complete the mental arithmetic questions within a certain time range, which can also enable the tester to enter the test state faster. In this experiment, data collection is combined with questionnaire survey and waveform diagram to intercept effective data.

4.2. Analysis of Experimental Results

4.2.1. Anti-Interference Effect. This article uses the ECG acquisition circuit and NI the RIO embedded development platform as the ECG acquisition equipment, among which the ECG signal leads use the right upper limb, right lower limb, and left upper limb. The ECG signals of 60 students were collected, and a total of 300 groups of ECG data were collected. After removing unstable signals, there were a total of 180 groups of valid data, including 90 groups of high-voltage data and 90 groups of low-voltage data. The 3000 sampling points during the calm phase of the tester were used as low pressure data, and the 3000 sampling points during the pressure induction process were used as high pressure data. Figure 4 shows the ECG waveforms of a subject under low pressure and high pressure.

As can be seen from Figure 4, the collected ECG signals under low-voltage and high-voltage conditions contain interference, but the degree of interference is low, which can more clearly obtain the ECG waveform state of students, indicating that this method can effectively identify the psychological stress state of college students. This is because the wavelet transform method is used to process the ECG signal in Section 2.1.2 of this paper. The ECG waveform without noise can be obtained from the processed waveform, so as to extract the pressure related features.

4.2.2. Recognition Accuracy Rate. During the recognition accuracy test, keep the laboratory environment quiet and the mobile phone silent. After the preparation is completed, start the mental arithmetic experiment. Mental arithmetic experiment is a quantitative analysis of psychological stress, which is divided into two states: no and there. The subjects first have a 60 s resting state, adjust to a calm psychological state, and then start the mental arithmetic task. The task content is the addition of six random three digits. The time of each task is 5 seconds, and the mental arithmetic is repeated 10 times, with a total time of 50 seconds. After the mental arithmetic experiment, the subjects took a short rest to adjust their psychological stress state. *M* P150 physiological parameter recorder was used to collect the ECG signals of subjects. The total number of samples collected in the recognition accuracy test is 60, and the proportion of the number of samples in the training set and the test set is set to 35 : 25. The methods in this paper, reference [8] and reference [9] are used to identify the psychological stress indicators of college students, respectively, and the recognition accuracy results are shown in Figure 5.

By analyzing the experimental result data in Figure 5, it can be seen that there are some differences in the accuracy of identifying s students' psychological stress indicators by using the methods of this paper, method in reference [8], and method inreference [9]. Among them, the highest accuracy of this method in identifying college students' psychological

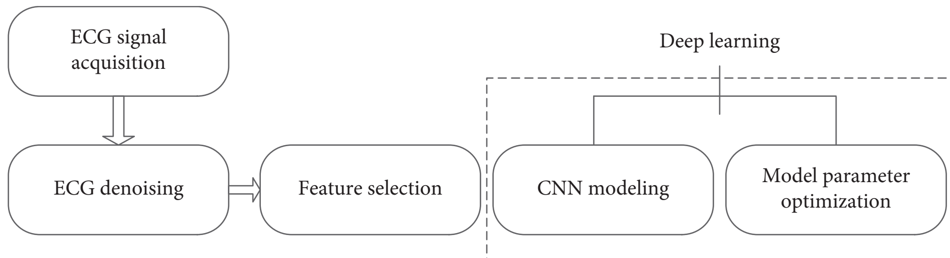

Figure 3: The process of identifying and modeling college students' psychological stress indicators.

Table 1: Subject information.

Education	Subject	Gender	
		Male	Female
Undergraduate	Engineering	12	7
Master	Liberal arts	8	5
Undergraduate	Engineering	9	6
Undergraduate	Liberal arts	7	8

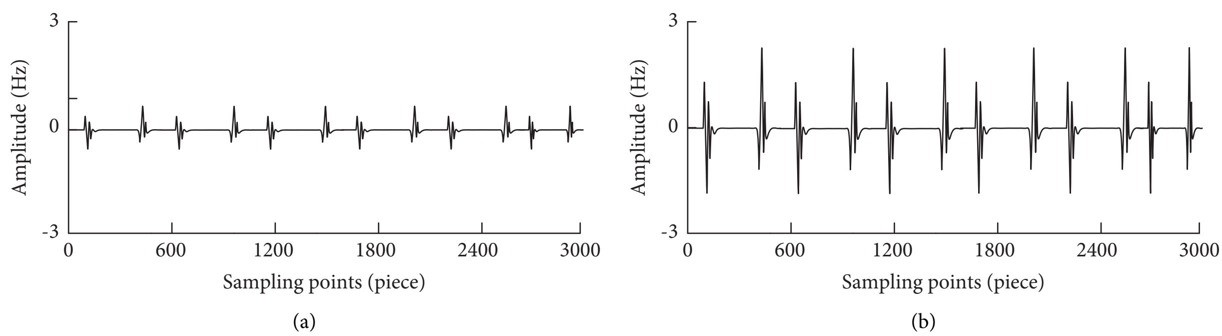

Figure 4: ECG waveforms of subjects in different states: (a) low pressure state; (b) high pressure state.

stress indicators is about 98%. Although the accuracy of method in reference [8] and method in reference [9] is within a reasonable range, it is always lower than this method, which verifies the effectiveness of this method. The reason for the high recognition accuracy of this method is that this method preprocesses with the psychological stress index of college students before constructing the model and uses the sequential backward selection algorithm to select the characteristics of psychological stress index, optimize the input data of the model, and further improve the recognition accuracy.

4.2.3. Identification Time. The optimal training parameters are as follows: the learning rate is 0.001, the number of iterations is 40, the inactivation rate is 0.5, and the vector dimension is 300. Based on the above parameter settings, the identification time of college students' psychological stress indicators identified by the methods in this paper, reference [8] and reference [9] is tested. The results are shown in Figure 6.

By analyzing the experimental data in Figure 6, it can be seen that with the change in the number of experiments, the time used to identify the psychological stress indicators of college students by this method is always less than 1.5 s, which is significantly lower than the methods in reference [8] and reference [9]. In contrast, the time-consuming of this method is relatively short, because the ECG signal is preprocessed before index recognition, which reduces the negative impact of interference signal and then reduces the recognition time of this method.

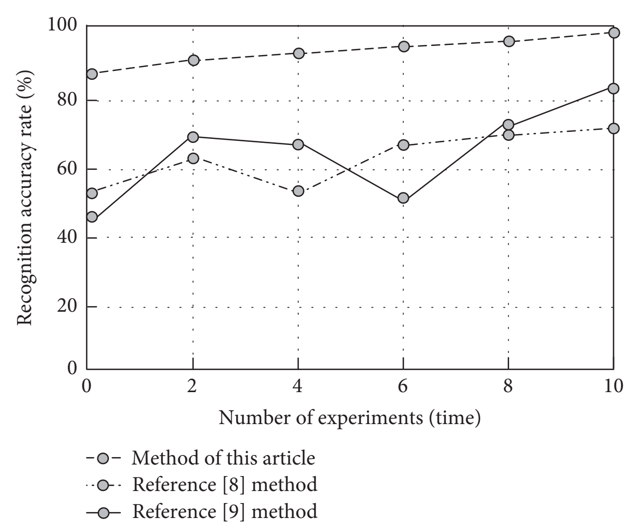

Figure 5: Comparison results of recognition accuracy of different methods.

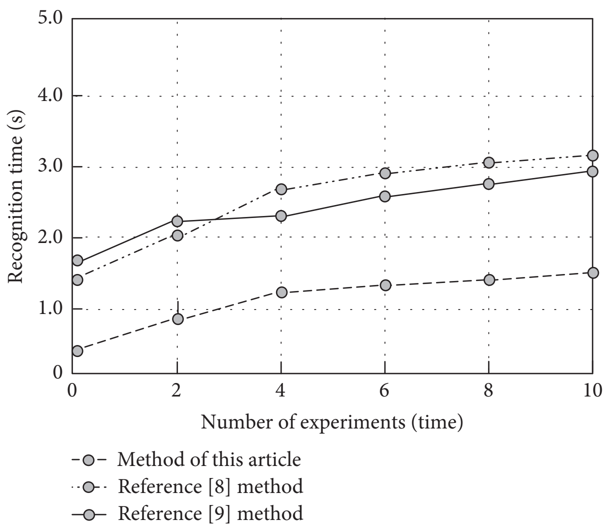

Figure 6: Comparison results of recognition time of different methods.

To sum up, the recognition result of this method has high accuracy, has high recognition efficiency, and is not easy to disturb, which shows that the recognition result of this method for college students' psychological stress index is stable and reliable.

5. Conclusion

Psychological index recognition and modeling, combined with the basic principles of psychological measurement and machine learning technology in computer field, will open a new door for psychological research. In order to improve the recognition effect and provide help for the diagnosis and treatment of college students' psychological problems, this paper proposes a deep learning-oriented identification and modeling method of college students' psychological stress indicators. Experiments show that this method has high recognition accuracy, has high recognition efficiency, and is not easy to be disturbed.

Although the experimental results show that the proposed method is feasible and its calculation results have been tested for reliability and validity, as a new method, it still has shortcomings. For example, massive user data can reach TB level. When processing and analyzing, the computing performance and storage performance of the computer will face higher requirements, which is also the focus of the next research.

Data Availability

The raw data supporting the conclusions of this article will be made available by the author, without undue reservation.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding this work."

Acknowledgments

This work was funded by Henan Province Philosophy and Social Science Program Youth Project: "Developmental dyslexia group text and face cognitive neural mechanism research" (2018CJY035).

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