An Abnormal Behavior Detection Method Leveraging Multi-modal Data Fusion and Deep Mining

Xinyu Tian, Qinghe Zheng and Nan Jiang

Abstract—**At present, the increasingly prominent mental health problems of college students have gradually become the focus of the society, universities and families. According to the current situation and challenges of mental health work of college students, we put forward the idea of constructing an early warning platform for college students' psychological crisis based on deep neural networks. The purpose of constructing this platform is to comprehensively improve the psychological health of college students and to purposefully prevent and intervene the psychological crisis. In this paper, we focus on describing the structure, composition of proposed platform and functions of each module, and then give a specific framework, training and testing scheme for the core part of the platform, which is the neural network model for real-time monitoring and analysis of students' mental health. Finally, we demonstrate the effectiveness of the deep neural network for analyzing behavior patterns through simulation experiments on the generated data set.**

Index Terms—**Abnormal behavior detection, multi-modal data fusion, deep mining, neural network**

I. Introduction

With the rapid development of education and the increasingly fierce competition, the mental health of college students have gradually become the focus of society, universities and families. And the mental health education has also gradually developed into an important and essential part of ideological and political work in research institutes and universities [1][2][3].

The mental health is a key connection during the process of college students' comprehensive development and growth [4]. Mental health refers to continuous and positively developing psychological states, in which the subjects can make good adaptations and give full play to their physical and mental potential. It is necessary to change the previous problem oriented concepts, and actively carry out the mental health education. Prevention and intervention of the psychological crisis [5][6] will comprehensively improve the psychological health of college students, through real-time analysis and supervision of the college students' mental health.

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A. Current Situation of Mental Health Education for College Students

The college students' mental tension and depression were caused by heavy academic pressures, severe employment forms, tense interpersonal relationships, the confusion and helplessness of the independent living. In recent years, the number of "campus incidents" such as violence, bullying, and suicide caused by psychological problems has been increasing [7][8][9][47][48], causing the varying degrees of harm to students, families, and universities. Therefore, the effective guidance, early warning, and timely control are urgently needed to solve the practical problems faced by college students' mental health. In this way, the probability of dangerous behavior of students is minimized, and the crisis is eliminated in the bud state. In other words, the purpose of maintaining the physical and mental health of college students, ensuring the safety of students' life, and the stability of the campus are achieved.

Since 2007, Peking University Health Science Center has established a three-level psychological crisis prevention and intervention system, consisting of psychological observers, head teachers or counselors, and professional psychological counseling centers. The system also puts forward higher requirements for psychological observers, head teachers, and counselors. It is necessary to master more psychological knowledge, and skills of observation and communication [10]. Liu et al. [11] proposed that MicroBlog can be used to identify and intervene college students' psychological crisis in the new media environment. This new kind of method can to some extent complement the deficiencies of traditional psychological education. However, this approach requires psychologists in college to be proficient in using MicroBlog and sensitive to the changes of students' psychology. It can be seen that the traditional psychological crisis warning and intervention model places high demands on psychologists (such as teachers and counselors). Without professionalism, they often miss the best time to intervene in a psychological crisis, leading to a crisis event.

B. Management Methods of Students' Mental Health Based on Big Data

In recent years, the successful application of big data in various fields has shown its incomparable advantages, such as financial analysis [12] [13], traffic management [14][15], medical diagnosis [16][17][18], etc. Reliable analysis and judgment based on a large amount of data support, would reduce costs, improve productivity and flexibility, or bring better decisions.

Similarly, a big data-based analysis system of students' psychological state is conducive to cultivating an optimistic, positive and healthy mentality. Zhang [19] designed and developed an analysis system for students' psychological health education based on massive data. This system is used to predict students' psychological and behavioral trends, but it does not give details of the composition of the big data and how it is established. Li [20] proposed to build an effective warning and intervening mechanism for college students' psychological crisis based on big data, and set up relevant mental health educators, to develop a targeted emergency response arrangement. However, specific technical details and implementation plans are not described. As a matter of fact, the analysis and research on students' psychological state based on big data is still in its infancy in China.

C. Contribution and Organization

We have changed the traditional problem-oriented concept and proposed the deep neural network based early warning platform for students' psychological crisis. Then students' mental health can be monitored and analyzed in real time by this platform. The establishment of a warning mechanism for psychological crisis can be targeted for expert intervention. Based on the big data of students' behavior and activities, a systematic early warning platform used for the prediction of students' psychological crisis can be set up, which integrates information collection, analysis, and warning. It can provide support for mental health education, helping psychologists to identify, intervene and alleviate the problem of students' mental health.

This paper is organized as follows. In Section II, we have summarized the related work in the field. Section III gives the construction process of building an early warning platform for psychological crisis. In Section IV, we introduce the analysis model of students' mental state based on deep neural network. Experimental results and analysis are presented in Section V. Finally, we conclude our work and discuss future directions in Section VI.

II. Related Work

Automatic recognition of human behavior has been studied in the field of computer vision for many years. Chen et al. [21] proposed an novel approach to detect human body by using contour information. At the same time, the mean shift method based on human body structure and historical motion image information is used to search the most significant features. In the end, the recognition accuracy of historical information can be greatly improved by combining Bayesian framework with support vector machine (SVM). In practice, abnormal crowd behavior detection plays an important role in public security monitoring and prevention. Xiong [22] proposed a camera parameter independent and perspective distortion invariant method to detect two kinds of abnormal behavior. The experimental results showed that the method can detect the abnormal behavior reliably under the condition of low computation without camera calibration and training data. Reliable data mining is one of the most effective methods to detect abnormal behaviors from massive data. A method for auditing users' behaviors based on data mining method was proposed by Wei et al. [23]. Moreover, Sun et al. [24] believe

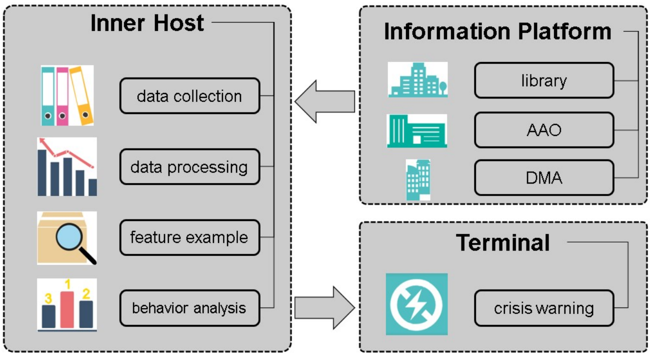


Fig. 1. The architecture of monitoring platform for students' psychological health.

that each behavior sequence is associated with some behavior labels, and the distribution of behavior labels covers a series of behavior labels, indicating that each behavior label describes the degree of description of the behavior sequence. In this way, managers can not only obtain what actions have taken place, but also take into account all actions of each action sequence. For advanced persistent threats (APTs), Tao [25] proposed an analysis method based on feature extraction and statistical modeling to describe the abnormal network behavior. In recent years, deep learning based methods have also shown unparalleled advantages in the field of intelligent data analysis. Wang et al. [26] used two stacked denoising autoencoders (SDAEs) to automatically learn the appearance and motion characteristics of an object, and constrained it to a space-time volume on the dense trajectory with rich motion information to reduce computational complexity. Shi [49] pointed out the practical problems faced by college students' psychological crisis early warning methods, especially the lack of specific application research on indicators in practical work.

III. Construction of Early Warning Platform

After a long period of practice, the current approaches of preventing and intervening psychological crisis, have played a certain positive role, but it has also gradually revealed its limitations, including psychological testing for freshmen, courses of mental health education, campus activities, and psychological counseling stations. In the traditional model, the main method of psychological crisis intervention is based on the results of freshmen's psychological tests, offline education, diagnostic scale and psychological counseling. But the reliability of the results is to some extent interfered by students' deliberate concealment and external environmental factors [27][28]. In other words, due to the large number of students, it is difficult for mental health workers to track, analyze and consult each student one by one in real time, most of them can only "passively" accept feedback from students with hidden psychological crisis [29-34]. At present, some colleges and universities have insufficient personnel for mental health education, and some of them are engaged in part-time psychological work. So, mental health education has not been carried out smoothly. Aiming at the above problems, we have proposed the establishment of early warning platform for students' psychological crisis based on deep neural network, which can be used to monitor and analyze students' mental health in real time and assist the

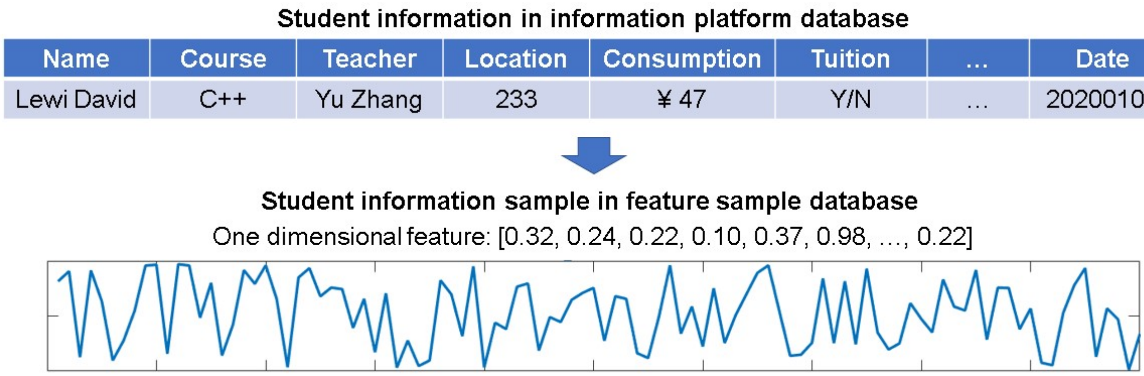


Fig. 2. A feature sample about students' activities.

smooth progress of mental health work. The details are given as follows.

A. Framework

According to the key requirements of information platform application, the architecture is composed of five functional modules: data collection module, data processing module, feature sample library, psychological state analysis model, and crisis early warning system, as shown in Fig. 1.

The data acquisition module is responsible for collecting all-round students' information while they are on campus. And the obtained raw data is passed to the data processing module for cleaning and preprocessing. Then build a feature sample library to help complete the construction of the mental state analysis model, including all aspects of each student's study, practice, reading, activities, consumption, etc. After the model is launched, the early warning system is responsible for feedback of the students' mental health. The use of this system can move the focus of mental health education in colleges and universities, and enable educators to work in a targeted. Through active prevention, effective intervention, and long-term evaluation, the students' physical health can be maintained.

The platform should have the following characteristics in the design process:

1. Intuitive and convenient interface.
2. Robust analysis model of students' psychological state.
3. Standards for executable database.
4. Portability for different systems.

B. Data Acquisition Module

Under the traditional model, the relevant data are mainly obtained through the results of general psychological tests at the time of enrollment and the consultation records of the psychological counseling center [35-37]. However, the physical and mental development of college students is in a transitional transition stage. Furthermore, their psychological state is easily affected by a lot of factors, such as complex environments and emergencies. Therefore, these raw data cannot truly reflect students' physical and mental health at all stages. Therefore, efficient use of these data as the basis for psychological intervention is contingent and delayed.

The data acquisition module of the early warning platform should be linked with the information platform of all college, collecting and transmitting all situations of students' daily learning and life without disturbing. These raw data include academic achievement, reading, sports, consumption, awards, practical and campus activities, violations of regulations, teacher comments. A strict confidentiality mechanism needs to be established to securely manage and effectively utilize students' information.

C. Data Processing Module

The collected data contains different types, such as text, numbers, English letters, and different storage formats. Therefore, the normalization of rough and raw data needs to be done through the following preprocessing methods.

The text data is first translated into numbers for storage according to the GB18030-2005 Chinese character encoding standard. Translate English letters into corresponding binary ASCII codes. The digital data only needs to be normalized to the range of [0, 1]. For the inconsistent format of the stored data, all collected data is read into the system and processed uniformly, and then output as a file in the form of spreadsheet to save.

D. Feature Sample Library

The information data generated by students during school are fragmented and distributed among various departments of the school, such as the Academic Affairs Office, Student Affairs Department, etc. Therefore, it is necessary to realize the unified collection and integration of data through the early warning platform, providing support for construction of the real-time monitoring and analysis model based on neural networks. A large database is need to build containing the following feature samples:

(1) Information of students' elective courses (*e.g.*, names, teachers, places of class), grades, and disciplinary actions recorded by the Academic Affairs Office.

(2) Social practice (including frequency, date, evaluation result), campus activities and competitions (including names, awards, dates, and level), difficulty identification, violations and disciplinary actions provided by the Student Affairs Department.

(3) Students' self-study time (such as entry time, exit time), borrowing books (title, type, time) in library.

(4) The time for students to enter and leave the apartment, and sport events in sports centers.

(5) Students' tuition, student loan provided by Financial Service.

(6) Students' housing situation managed by Dormitory Management Committee.

(7) The usage of network during the school viewed in Information Center.

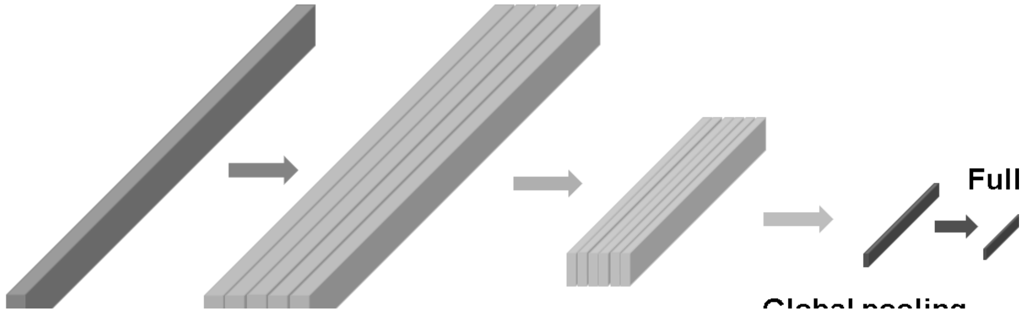


Fig. 3. Structure of deep convolutional neural network model.

(8) Psychological test results, consultation records, clinical scale obtained by Psychological Counseling Center.

All the feature examples are finally concatenated into a one-dimensional vector and saved in the spreadsheet. An example has been shown in Fig. 2. In the process of storing and using, the security and confidentiality of sensitive data should also be strengthened. These data can be managed securely through using operation record, separate storage, encryption transmission, and regular audits. Through the establishment of a database containing feature samples, the effective integration, sorting, and storage of various data of student life and learning are prepared for subsequent analysis and mining.

E. Early Warning System

According to the student's psychological status fed back by the psychological state analysis model, we use four kinds of colors (*i.e.* green, yellow, orange, and red) to represent different levels of psychological crisis alert states.

Green color is for "normal mental state". Yellow color represents "low-risk alert state", which means that student had great fluctuations in psychology, and is easily affected by surrounding environmental factors, and may even cause serious psychological crisis. Therefore, the counselors and psychological educators should timely communicate with he or her to relieve his or her bad emotions. Orange color stands for "moderate alert state". Secondary colleges are needed to intervene by psychological consultation from professionals for effective precautions, and inform the parents. Red means "high-risk alert status". The parents of the student should be notified immediately, and this student should be safely transferred to a professional hospital for treatment to prevent accidents.

IV. Analysis Model of Psychological State

A. Structure of Deep Neural Network Model

Considering the size of students in a single university and the amount of data collected by day, we have established a 150 layer residual neural network model ResNet [38] : $f(\cdot)$. The larger the data, the deeper the network model is needed to fit, to ensure that the model is fully optimized and the new test data is well generalized. The model consists of an Input Layer I, 150 Convolutional Layers C1-C15, three Pooling Layer P1-P3, a Global Average Pooling Layer G, a Fully Connected Layer F, and an Output Layer O, as shown in Fig. 3.

The specific parameters of the network model ResNet are set as follows.

(1) The input signal is a 1 × 512 vector used to characterize the daily activities of students, so the size of Input Layer is 1 × 512.

(2) In the Convolutional Layers, C1-C5 contain 128 convolutional kernels; C5-C10 contain 256 convolutional kernels; and C10-C15 contain 512 kernels. The size of these convolution kernels is all 1×1. The step is set to 1, each convolutional kernel contains one parameter θ that can be updated.

(3) The maximum sampling operation in Pooling Layer is achieved by setting the step to 2 and the size to 1×2, which is used to reduce the dimensionality of features in the process of knowledge transfer.

(4) In Global Average Pooling Layer, the final eigenvector is averaged by convolution kernel and connected to FC with 24 neurons.

(5) Add a non-linear activation function PReLU [39] after each hidden layer to achieve the non-linear transformation for the previous output. It is defined as follows:

$$y = \begin{cases} x, & x \geq 0 \\ \delta x, & x < 0 \end{cases} \tag{1}$$

where δ is a parameter that can be updated during training, and used to avoid the phenomenon of "neuron necrosis" in the traditional training process, that is, certain neurons cannot be further trained once they have a negative output.

Finally, there are four neurons in the output layer, which represent the four states of "normal mental state" (that is, [1,0,0,0]), "Low-risk alert state" ([0,1,0,0]), "Medium-risk alert state" ([0,0,1,0]), and "High-risk alert state" ([0,0,0,1]). Then the analysis results of students' psychological condition by the deep neural network model can be output through the Softmax function [40]:

$$p_i = \frac{e^{x_i}}{\sum_{j=1}^{4} e^{x_j}}, i \in [1, 2, 3, 4] \tag{2}$$

where x_i represents the component of the final feature vector whose dimension is denoted by i, the $[p_1, p_2, p_3, p_4]$ represents students' mental state fed back by the deep neural network model. So far, the structure and composition of the model have been introduced.

B. Training Procedure

The deep neural network model is composed of layers of

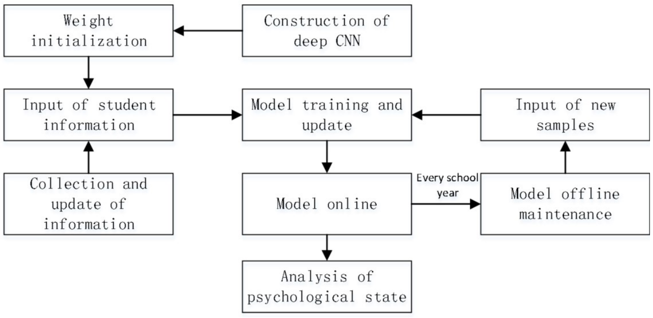


Fig. 4. Establishment and working procedure of the deep convolutional neural network model.

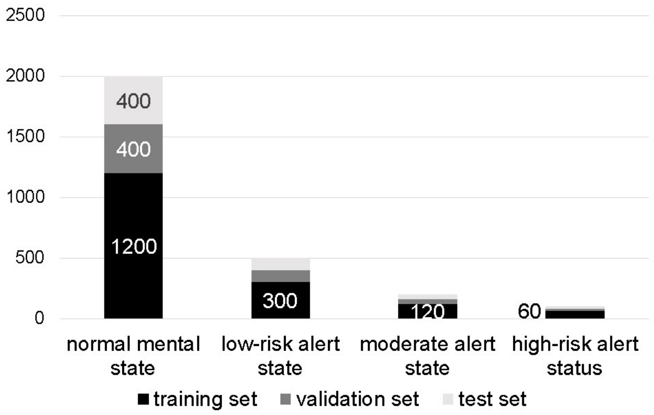


Fig. 5. The division of sample set.

nonlinear transformations. Therefore, the students' behaviors can be automatically analyzed, and the potential information behind a series of data is mined, to complete the capture of students' psychological state. The full training of model is a necessary condition for application in real life. The small batch stochastic gradient descent based on back propagation is one of the most commonly used methods for neural network training.

First, we need to compute the model's optimization goal after the current iteration process, that is the loss function. It is defined as a cross-entropy function with L2 regularization:

$$\mathcal{L} = -\frac{1}{M}\sum_{i=1}^{M}\sum_{j=1}^{4}\mathbf{y}_i^j \log\left[f^j(\mathbf{x}_i)\right] + \frac{\lambda}{2}\sum\|\theta\|_2 \tag{3}$$

where $\mathbf{y}_i$ represents the category label of the mental state corresponding to the i-th data input into the network. It can be determined by the freshmen' psychological test results. $f(\mathbf{x}_i)$ represents the analysis result of the neural network model. λ is a hyper-parameter that used to determine the intensity of regularization, and is usually set to 0.0005. Then we use the obtained loss function to calculate the gradient value of the current batch of data. Assuming at the t-th training iteration, the gradient value is:

$$\nabla_{\theta_t}\mathcal{L} = \sum_{i=1}^{4}\left[f(\mathbf{x}_i) - \mathbf{y}_i\right] + \lambda\theta_t \tag{4}$$

Next, according to the current gradient, the weights of the deep neural network model are updated in a backpropagation manner [41][45]. The updated weight can be calculated by:

$$\theta_{t+1} = \theta_t - \alpha \cdot \nabla_{\theta_t}\mathcal{L} \tag{5}$$

where α is the learning rate and is used to determine the speed of gradient descent. Then we can repeat the above steps, i.e., continue training the deep convolutional neural network model cyclically, and updating the weight parameters, until the loss value no longer drops on the training set, the whole training process can be stopped. Finally, the convergent deep convolutional neural network model $f^*(\cdot)$ is obtained through continuous training.

C. Testing Procedure

After the model is trained locally, it can be deployed on a psychological crisis early warning platform to complete the real-time analysis and supervision of students' mental health status. The processed students' daily activity information $\mathbf{x}$, collected by the fore-end, can be input into the deep neural network model. Then we can output the student' mental state analysis result $f^*(\mathbf{x})$. The overall flow of the model is plotted in Fig. 4.

Then, all the students' abnormal behavior can be analyzed, monitored, and timely warned by the proposed early warning platform. In this way, important early warning information can be provided by platform's sensitive tentacles, assisting colleges' educators to understand the students' "unhealthy" psychological status in a targeted and active manner. As a result, educators can effectively help students to unblock and resolve bad emotions in a timely manner, and overcome difficulties in learning and life, and establish an optimistic, positive and upward mentality.

From student enrollment to graduation, the educators can long-term track and evaluate students' mental health from multiple perspectives, multiple orientations. The scientific prevention and intervention of psychological crisis, effective intervention of the psychological crisis in the budding period can be achieved through using this platform. Thereby, the physical and mental health of students can be improved, and a safe, harmonious and civilized campus environment can be established.

V. Simulation and Analysis

A. Experimental Dataset

For the sake of privacy and security of college students' information, we synthesize the simulation data satisfying the specific distribution to verify the effectiveness of proposed method, i.e., 150-dimensional vectors. In fact, only a small number of college students have psychological problems and lead to excessive behavior in real life. Therefore, this kind of problem can be regarded as a four category classification problem with seriously unbalanced data.

In this case, we generate 2000, 500, 200, 100 samples for the four categories ("normal mental state", "low-risk alert state", "moderate alert state", and "high-risk alert status"), respectively. The training set, validation set, and test set are divided according to the ratio of 6:2:2, as shown in Fig. 5. The training set is used to complete the training of the deep learning model, that is, to update the weights. The validation set helps determine the appropriate hyper-parameters, including learning rate and batch size. Test set is used to evaluate the effectiveness of the algorithm. In order to facilitate training process, the values of all samples are normalized to between 0 and 1.

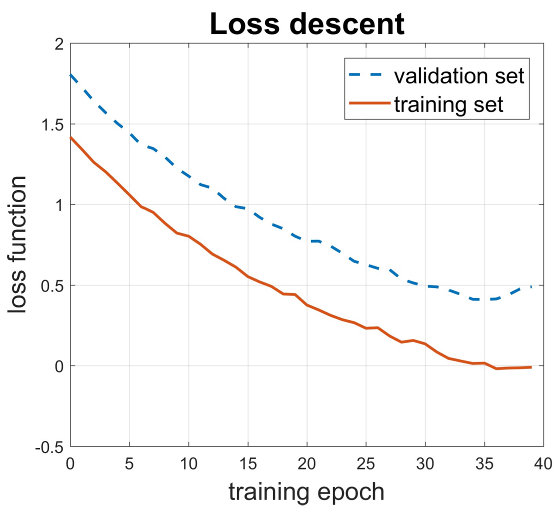


Fig. 6. Training curves of deep convolutional neural network.

TABLE I
PERFORMANCE OF CONVERGENT DEEP CNN

Sets	Loss	Classification accuracy (%)
Training set	0.12	96.64
Validation set	0.44	90.27
Test set	0.47	88.60

TABLE II
COMPARISON OF DIFFERENT MACHINE LEARNING MODELS

Methods	Classification accuracy (%)
SVM	85.37
Random forest	87.94
Decision tree	81.22
Deep CNN	88.60

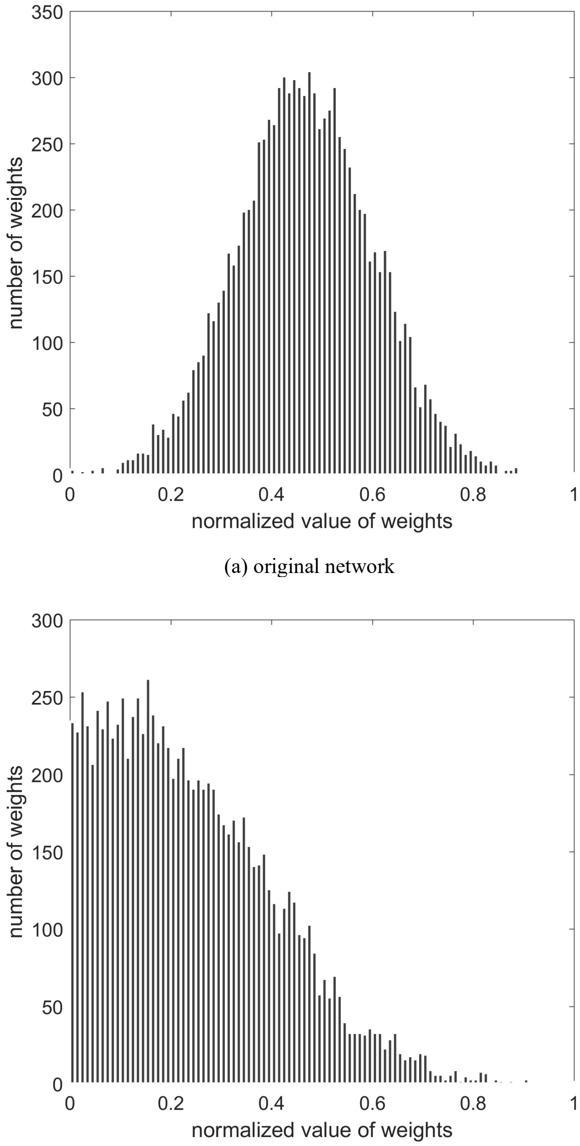
B. Experimental Setup

All the training and testing process of deep convolutional neural network are carried out through Matlab 2019a with a workstation consisting of Intel Core i7-9700 CPU, Nvidia GeForce GTX 1660 6G, 16-gigabyte memory and 1-terabyte storage.

At the beginning of training process, the hyper-parameters are set as follows. Learning rate is set to 0.01 and decreases exponentially; mini-batch size is set to 64; weight decay is set to 0.0005 to reduce the degradation of generalization ability caused by over-fitting problem. When the loss of the training set is still declining while the classification accuracy of the validation set starts to rise, the training will stop within five training epochs. To evaluate the generalization capacity of the deep learning model, no data augmentation technology is used in the training process.

C. Experimental Results

We first present the training curves of deep convolutional neural network, as shown in Fig. 6. Due to the small training set size, the entire training process ends within 40 epochs. It can be seen that there are over-fitting problem in the model starting from 35 epochs, i.e. the loss of training set gradually decreased while that of validation set began to increase. In fact, the gradient of training becomes more and more sparse: from the top layer down, the error correction signal becomes smaller. The model still has generalization errors in the end, due to the noises of the correlation between the labels and categories. Generally speaking, the more data there are, the smaller the generalization error of the model will be. This is also a key factor affecting the performance of the model.



(a) original network

(b) convergent network

Fig. 7. Distribution of weights in deep convolutional neural network.

Then we report the loss and classification accuracy of the training set, validation set and test set of the convergent deep learning model, as shown in Table I. At the end of the training process, the training loss and validation loss are 0.12 and 0.44, respectively. The corresponding generalization error reaches 0.32, which is acceptable. Finally, the proposed deep learning based method achieves the classification accuracy of 88.60% on the test set.

D. Discussion

Deep learning based methods usually have a strong data mining ability in the face of big data. However, the amount of our simulation data is limited. In this case, we compare a variety of traditional machine learning algorithms to observe the performance of deep learning, including support vector machine (SVM) [42], random forest [43], and decision tree [44][46].

The experimental results are shown in Table II. By contrast, the deep learning method still performs best. Although the number of samples is not particularly large, the dimensions of the samples reaches 150. The correspondence between the category labels and samples is difficult to map by simple linear transformation. As one of the most popular typical severe over-parameterized models, the deep learning model can excavate hidden expert knowledge well.

In order to understand the nature of the neural network, we observed the distribution of 10000 normalized weights of the model, as shown in Fig. 7. It can be seen that the weights of the original network are initialized according to the Gaussian distribution. By comparison, the weights of the convergent network are mainly concentrated near smaller values (i.e., less than 0.5). Under the same network architecture, larger weight values bring more complex decision-making surfaces, while smaller weight values result in relatively flat decision making surfaces. In other words, smaller weight values mean a lower model complexity, therefore the deep convolutional neural networks can be well generalized on unseen data in practical applications.

VI. Conclusion

In response to the increasingly prominent psychological health problems of college students, as well as the current status and challenges of psychological health education in universities, we put forward the idea of building a big data platform for students' psychological monitoring based on deep neural network. The structure and composition of the platform and the functions of each module have been mainly described. The structure used for analyzing and monitoring students' mental state is designed and specific training and testing programs are introduced in detail.

Using the advantages of rapidity, relevance and accuracy brought by big data and deep learning algorithms, educators can quickly and effectively analyze the psychological state and degree of danger; prevent and intervene psychological crises more efficiently and more targeted; cultivate more college students to establish a healthy, optimistic, positive and upward mentality; and build a safe, harmonious and civilized campus. This also provides guidance for further research and development of students' mental health service platforms based on the Internet, the Internet of Things (IoTs) and big data in the future.

Although the research is based on simulation data, we will establish reliable and practical standard for building platform and collecting data in the future research. The focus of future work is to further establish and improve the corresponding analysis mechanisms in terms of whether the privacy of students can be guaranteed and whether the psychological burden of students will be increased.

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