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Exploration of a Multidimensional Early Warning System for Higher Vocational Students' Mental Health by Integrating AI Behavioral Recognition and Multilayer Perceptual Network Algorithms

Xiulian Fang[1,*] and Yukun Sun[1]
[1] Quanzhou Ocean Institute, Quanzhou, Fujian, 362700, China
Corresponding authors: (e-mail: xiulianfang2025@163.com).

Abstract The current problem of students' mental health has attracted more and more attention, and students' psychological warning is one of the most important means to ensure students' mental health. This paper obtains research data based on the questionnaire method, utilizes multiple preprocessing methods to process the data, and at this level, uses the global chaotic bat algorithm to complete the data feature selection. The selected features are put into the Res-MLP network for training, and finally the artificial intelligence behavior recognition model based on Res-MLP is designed. Combining the model of this paper and the related development software, the multidimensional early warning system for the mental health of higher vocational students is designed and the system of this paper is verified and analyzed. The system still has excellent response time in the face of high number of concurrency, with a value of 1.332s, while also taking into account the excellent security performance, the system in this paper can better serve the higher vocational mental health education.

Index Terms global chaotic bat algorithm, Res-MLP network, early warning system, mental health

I. Introduction

Psychological crisis refers to the individual encountered with events or situations with significant psychological impact, the use of existing psychological resources can not effectively respond to, and then cause cognitive, emotional, somatic or behavioral imbalance or dangerous state [1]. Higher vocational college students are in the critical period of personality development and shaping, behavioral habits formation, psychological conflict resolution, heavy learning tasks, facing numerous pressures, and are more likely to produce a strong stress reaction, which in turn leads to psychological crisis [2]-[4]. Their psychological confusion focuses on adaptive and developmental psychological problems, including the inability to change learning styles in time, the inability to adapt to new living environments, difficulties in emotional management, frustration in love, disharmony in interpersonal relationships, and the lack of career planning [5]-[7]. Teachers in higher education should pay attention to such psychological conditions of students in time, and give more attention, guidance and intervention according to their mental health characteristics. The establishment of a mental health early warning system for higher vocational students is the basic link in the whole psychological crisis intervention system, which can play an early warning role [8], [9]. By monitoring the psychological dynamics of all students, according to certain early warning indicators, analysis and research of early warning information, screening the early warning object and scope, timely detection and identification of a variety of potential or actual crisis factors in students [10]-[12].

With the development of the times, artificial intelligence technology provides new research methods for mental health education. Higher vocational colleges and universities can take advantage of the construction of smart campus, using new technologies such as data monitoring, equipment monitoring, and Internet of Things to collect and organize college students' daily activity and behavior data in a timely manner [13], [14]. Through the establishment of an information-based mental health early warning system, timely detection of changes in students' mental health status, screening out psychological crisis information, and helping them to resolve ideological contradictions and psychological barriers are of great significance in improving students' psychological quality and avoiding the occurrence of psychological crisis events on campus [15]-[17].

In this paper, a questionnaire is taken to collect the research data, the data is normalized and balanced, and the global chaotic bat algorithm is used to select the features of the processed data so that it meets the criteria for recognition model modeling. Combining the feature data and Res-MLP network together to complete the artificial intelligence model design work. The overall framework of the mental health multidimensional early warning system was first determined, and the task of building the system was finally realized with the support of the model in this paper and the development software. After verifying the superiority of this paper's model, the system of this paper is then validated and analyzed from two aspects: response time and safety performance.

II. Mental health data processing and feature selection

II. A. Mental health data processing

II. A. 1) Data acquisition

This experimental study was conducted on people over 18 years old, and the dataset used was obtained from the online design of questionnaire recycling over a period of three months, with a deadline of August 2023, and a total of 1,596 pieces of completed data were finally recycled. The dataset is mainly composed of three parts: personality trait information, psychological state information and behavioral state information.

II. A. 2) Pre-processing of data

In the questionnaire assessment, there are always a variety of reasons that affect the integrity of the final scale data obtained. In this project, the following steps are taken to preprocess the raw data for the data with abnormalities, and the specific process is as follows:

(1) Data screening

When analyzing massive data, we generally do not need to use every attribute of the original data set. This is because the preliminary data collection work is to collect as much and comprehensive data as possible, and the specific use of the data is not carefully considered. Whereas, with a specific research objective, there is a need to filter the data needed for that research objective. For example, in this research, the demographic information filled in by the testers, such as age and gender, is high-quality and valid data, while the completion time, login location, browser type, etc. recorded in the background of the network are data that are not useful for this research.

(2) Data Cleaning

Data cleaning, i.e., data screening process after the data accidental errors, such as data inconsistencies, data anomalies, missing data and so on, resulting in poor data quality. In this process, different processing measures are generally taken for different situations, mainly missing value processing, outlier processing, data duplication processing, data inconsistency processing and other methods. In this paper, the collected outlier data are processed as follows: first, if an original data is missing more than 3 relevant attributes, delete it. Second, the original data with missing type of numerical type are filled with mean value, and the original data with missing type of string type are filled with multitude value. After the above processing, the final obtained experimental valid data 1538.

(3) Data integration

In practical applications, data may come from multiple data sources, at this time we need to integrate data from different data sources to create a unified data set. This integration is generally achieved by merging, de-weighting and reorganizing data from multiple data sources. The key to data integration is to ensure the consistency, integrity and reliability of the data, to provide data to facilitate the operation of the subsequent establishment of the model.

(4) Data conversion

Data conversion, also known as data mapping process, that is, data in different application scenarios need to be transformed in different ways, in order to better play the performance of the modeling algorithm. The most common is the conversion of text data, the computer can not directly deal with text data, so you need to encode the text data in accordance with certain laws so that the computer to perform.

II. A. 3) Normalization of data

Normalization of data, also known as normalization, is an operation that involves scaling the data range to a specific range, usually [0, 1] or [-1, 1]. This processing method can make different features have the same feature scale, to avoid problems due to different scales of the data itself. Currently there are a variety of normalization methods, the commonly used method is the min-max normalization method, the conversion function is as follows:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

where x' is the scaled value, x is the original data value, $x_{\min}$ is the data minimum, and $x_{\max}$ is the data maximum. The min-max normalization method scales the data to a specified range by subtracting the minimum value from each data point and dividing by the difference between the maximum and minimum values [18].

II. A. 4) Balancing of the data

Data balancing processing refers to the process of model training, through a variety of technical ways to make the corresponding data samples reach a balanced state, so as to improve the accuracy and stability of the model. In the actual data collection process, due to various reasons, the number of data samples of different attribute classes is very likely to be unbalanced. Especially in the binary classification problem, the number of samples of one category may be much more than the number of samples of another category. This data imbalance can lead to bias in the training and evaluation results of the model, thus reducing the accuracy and reliability of the model. Therefore, we need to balance the data to minimize the problem of poor performance of the warning model due to data imbalance.

II. B.Feature selection based on global chaotic bat algorithm

The Global Chaotic Bat Algorithm (GCBA), a heuristic algorithm, applies feature selection in the following steps: first, a chaotic mapping method is introduced in the initial stage to ensure that the bat population explores the entire solution space and to enrich the population diversity. In addition, a fitness function based on accuracy and feature subset length is used to calculate the score of the feature subset after each update. The Global Chaotic Bat Algorithm (GCBA) then selects the highest scoring feature subset by calculating the score, thus effectively eliminating irrelevant and redundant features from all feature variables [19].

This new method not only enriches the population diversity, but also ensures the uniform distribution of the population in the solution space, which helps the algorithm to avoid local optimization and obtain better convergence results. Its mathematical model is:

$$u_i^w = |1 - 2 \times (u_i^{w-1})^2| \tag{2}$$

where $u_i^w (i = 1, 2, \cdots, n, w = 1, 2, \cdots m)(u_i^w \in [0,1])$ is a chaotic variable, n stands for the number of bat populations, and w stands for the initial population dimension. Next, the inverse mapping of u_i^w can be performed to obtain the position of bat individuals in the solution space x_i^w, and the formula for x_i^w is:

$$x_i^w = k_i + (p_i - k_i)u_i^w \tag{3}$$

where p_i and k_i are the maximum and minimum values in the range of variables, respectively. When individual bat positions are updated, the local optimal positions of individual bats and the global optimal positions of the population are recorded. The position of the i bat at the $t+1$th iteration can be calculated by the following equation:

$$x_i^{t+1} = x_i^t + v_i^{t+1} F_1 c_1 (O_i - x_i^t) + F_2 c_2 (O_g - x_i^t) \tag{4}$$

where $F_1 = F_2 = 1.496$, O_i is the locally optimal position of the ith bat, and O_g is the globally optimal position of the bat population. c_1 and c_2 are two random values in [0, 1].

When the global chaotic bat algorithm is applied to feature selection, the bat population is initialized with a matrix of size $n \times m$. Where n is the number of bat populations and m is the number of features. The binary discretization of bat locations is then performed using the transfer equation. The transfer equation is:

$$S(x_i^w(t)) = \frac{1}{1 + e^{-x_i^w(t)}} \tag{5}$$

where $x_i^w(t)$ represents the position of the ith bat in the wth dimension at the tth iteration. The update equation for the position of an individual bat is:

$$x_i^w(t) = \begin{cases} 0, rand < S(x_i^w(t)) \\ 1, rand \geq S(x_i^w(t)) \end{cases} \tag{6}$$

where rand represents a random number within [0, 1]. When the position of the ith bat in the w-dimension is 0 at the tth iteration, the bat is not selected. When the position of the ith bat in the w-dimension is 1, the bat is selected.

III. Construction of a mental health early warning system

III. A. Algorithms for Multilayer Perceptual Networks

III. A. 1) Input layer

The input layer inputs data for the entire MLP network, generally the data is in the format of an array, the sensor signals used in this paper are one-dimensional arrays, while images or videos etc. are two-dimensional or multi-dimensional arrays when they are used as inputs [20]. Data needs to be preprocessed before inputting into the MLP, a common operation is normalization, which can speed up the convergence of the network, compressing the input data to [0, 1] directly for better extraction of the features, which is given by the formula:

$$x = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{7}$$

Where x is the current data, $x_{\max}$ refers to the data maximum and $x_{\min}$ refers to the data minimum.

III. A. 2) Full connectivity layer

In the MLP network, all layers are composed of fully connected layers, and each neuron linearly processes the high-dimensional information output from the previous layers to perceive the feature information of the previous layer. The fully connected layer can be used as a hidden layer to extract data features, or as the last layer of the model to act as a “classifier” using the Softmax activation function.

III. A. 3) Batch Normalization Layer

Batch Normalization Layer (BN), is a technique commonly used for neural networks to normalize the data prior to performing each layer of training in order to make the data distribution consistent. The learning of neural networks is essentially learning the distribution of the data, and in the training process, the data is usually fed into the network for training with each batch (Batch) of data, and different batches of data tend to have different distributions, which requires that the neural network needs to learn to adapt to the different distributions in each iteration, or else the changes in the distribution of the inputs at each layer will result in covariance bias, which will greatly reduce the network's training speed. The BN layer serves to force the data back to a normal distribution with a mean of 0 and variance of 1. This not only keeps the data similarly distributed, but also avoids the problem of vanishing gradients.

III. A. 4) Activation functions

Typically, the Sigmoid activation function is used to deal with binary classification problems, while the Softmax activation function is used to deal with multiclassification problems [21]. It is usually used in the output layer of a neural network to convert the output vector of the penultimate layer into a normalized probability distribution for classification prediction.

$$f_{Soft\max}(X_i)=\frac{\exp(X_i)}{\sum_{j=0}^{K}\exp(X_i)} \tag{8}$$

where X_i is the input vector of Softmax, consisting of $(X_1, X_2, ..., X_K)$, K is the number of classes in the multi-classifier, and $\sum_{j=0}^{s}\exp(X_i)$ is the sum of all probability values for the jth element.

III. A. 5) Loss function

The most commonly used loss function is the cross-entropy loss (CE) function, which is often used in multicategorization tasks together with the Softmax function. The expression of the cross-entropy function is as follows:

$$\mathrm{L}_{CE}=-\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{n}[p(x_{ij})\log(q(x_{ij}))] \tag{9}$$

where m is the sample size in the current batch, n is the number of categories, x_{ij} is the input sample, $p(x_{ij})$ is the true label of the sample, and $q(x_{ij})$ is the probability distribution of the model prediction. When the model's prediction $q(x_{ij})$ is closer to the true label, i.e., when $q(x_{ij})$ is close to 1, its information entropy is smaller, indicating more certain information. On the contrary, when the gap between $p(x_{ij})$ and $q(x_{ij})$ is larger, the information entropy is larger and the information is more uncertain.

III. B. Artificial Intelligence Behavior Recognition Model

III. B. 1) Res-MLP network

In order to solve the problem of high complexity of deep learning models currently used in mental health warning systems, this paper designs an artificial intelligence behavior recognition model based on multilayer perception algorithm (MLP) and residual network (ResNet). The residual network can effectively solve the network degradation problem and improve the performance of the model, and at the same time, the complexity of the model is greatly reduced because the model does not use the convolution and self-attention mechanisms and consists of only the simplest fully-connected layers.The dimensionality of the input layer of the complete network of Res-MLP is set to (7352, 561) to adapt to the dataset. The network uses two Res-MLP modules, where the fully connected layer of the first Res-MLP module is set up with 128 neurons and the fully connected layer of the second Res-MLP module is set up with 64 neurons.The tensor output from the Res-MLP module goes into a fully connected layer with 6 neurons and a Softmax activation function for classification. To prevent overfitting, the Dropout layer is set to 0.5, i.e., there is a 50% probability of temporarily dropping neurons.

III. B. 2) Overall framework

Firstly, signal data samples are collected from through questionnaires. Secondly, the collected data are preprocessed, including cleaning, normalization and other operations, while the global chaotic bat algorithm is used to complete the feature selection work, so as to produce a dataset suitable for training. Finally, the produced dataset is input into the lightweight Res-MLP neural network for training, and the model can be used to recognize human behavior after the training is completed.

III. C. Mental Health Multidimensional Early Warning System Design and Implementation

With the support of mental health data, artificial intelligence behavioral recognition model, and development software, this subsection will design and implement a multidimensional early warning system for mental health. The details are as follows:

III. C. 1) Overall system design structure

The system is mainly composed of three parts: data acquisition module, data preprocessing module and mental health identification and warning module. The psychological early warning system uses questionnaires or psychological tests to obtain data, preprocesses the collected data, including cleaning, normalization and other operations, and completes feature selection with the help of the global chaotic bat algorithm to construct an artificial intelligence behavior recognition model based on the Res-MLP network, which is capable of real-time updating of the monitoring object's psychological data with a good timeliness. At the same time, the data acquisition mechanism of the system also determines that its early warning of psychological problems will be more timely.

III. C. 2) Overall system implementation

Artificial intelligence, as a powerful technological tool, can be automated to mine and analyze large amounts of mental health data and identify potential abnormal patterns and risk signals from it. A large amount of college students' mental health data is collected, cleaned and processed to ensure the accuracy and reliability of the data. Then, data mining and machine learning algorithms are applied to analyze and mine students' psychological state and behavioral characteristics. Finally, these features are used to construct an early warning model to monitor students' emotions, language, behavior and other information, issue timely alerts and send reports to the relevant personnel, and provide decision support for the relevant personnel.

IV. Exploratory Analysis of Higher Education Students' Mental Health

IV. A. Validation Analysis of Artificial Intelligence Behavior Recognition Models

IV. A. 1) Data sets

The experimental protocol of the dataset was based on the Trier social task and the video-guided task to stimulate the psychology of the experimental subjects, and the physiological signals under different conditions, such as baseline, recreational, tension, and meditative states, were collected from the subjects in nearly 2 hours, and the subjects were asked to avoid coffee and nicotine intake before the experiment. Figure 1 demonstrates the waveforms of data under different experimental conditions for a subject in dataset A. It can be intuitively seen that there are large differences in the waveform characteristics of the four different psychological states, namely, baseline, recreation, tension, and meditation, in which the waveforms of the data have the highest frequency in the tension state and the lowest in the meditation state, and the slope of the data in the recreation state is steeper in comparison with the baseline. This also justifies the data set to some extent.

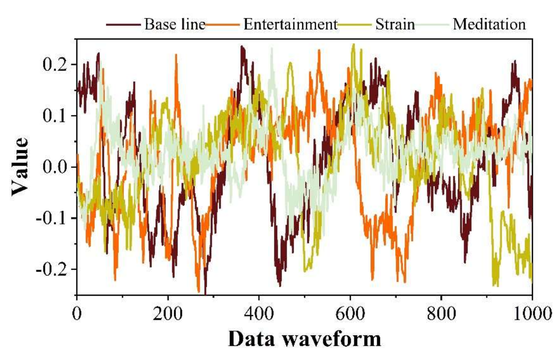

Figure 1: Data waveform

The questionnaire file provides the subjective scores of the experimental subjects on their own mental state status under each stage of the experimental process at that time, using the assessment questionnaire. pkl file provides all the data and corresponding labels of the experimental subjects. In this paper, we chose to collect and preprocess data based on the pkl file corresponding to each experimental subject because the labels and data in the pkl file are stored using arrays, which makes it easy to establish one-to-one pairs of data and labels. Through the setting of different experimental processes and conditions mentioned above, four different psychological states of the experimental subjects were stimulated, which provided the data basis for the construction of the mental health state recognition model in this paper, and the corresponding psychological state labels were 1, 2, 3, and 4, respectively, with 1=baseline, 2=stress, 3=recreation, and 4=meditation, and their data volume and data distribution are shown in Fig. 2. Most of the mental state recognition experiments realize two-classification (baseline, tension) and three-classification (baseline, tension, entertainment), and the meditation state is ignored, mainly because the data waveform characteristics of the meditation state, entertainment state, and baseline state are more similar, which brings more confusion in the recognition, so further completing the four-classification on the basis of the original classification is bound to bring about a certain decrease in the accuracy rate, however It has different significance for the subsequent in-depth research and analysis of the recognition of different mental states.

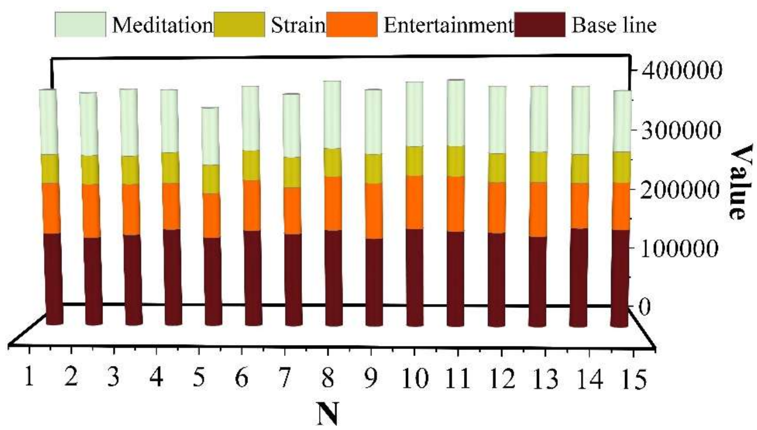

Figure 2: The amount of data for each mental state

The comparison of the number of experimental data before and after the balancing treatment is shown in Fig. 3. In addition to the balancing treatment, the data of the experimental subjects need to be divided into time windows before the psychological state feature extraction. The dataset A used in this paper is divided into a fixed window size in order to facilitate processing, and this paper takes every 20 seconds of continuous data as a data sample, i.e., 8500 sampling points. The sampling frequency of dataset B is 125 Hz, the same time window, each sample data is 1500 sample points, after processing the sample as the input for the subsequent model building in this paper.

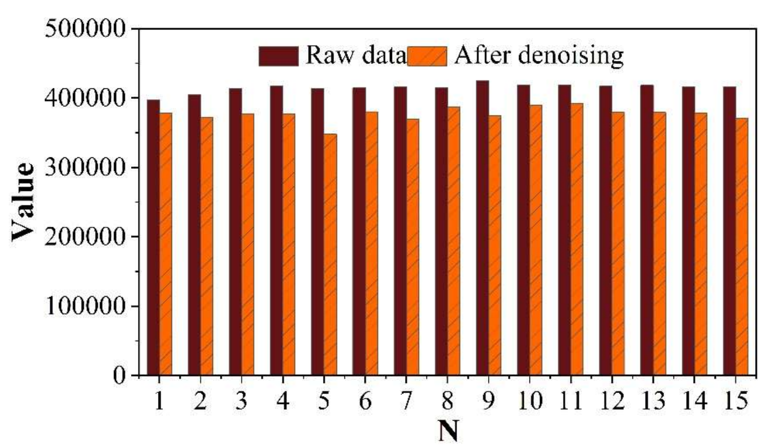

Figure 3: Comparison of experimental data before and after denoising

IV. A. 2) Comparison of the results of identifying psychological crisis states of higher education students

The experimental results were analyzed by using the correct rate of recognition, misrecognition rate, and refusal rate of the psychological crisis state recognition of senior students. The results of each senior students' psychological crisis state recognition experiment were counted separately, and the correct rate of recognition, misrecognition rate, and refusal rate are shown in Figures 4 to 6 respectively. From Fig. 4~Fig. 6, the correct rate of recognition, the rate of misrecognition, and the rate of refusal of recognition of the psychological crisis state of higher vocational students can be seen:

(1) The correct rate, misrecognition rate, and refusal rate of the support vector machine for recognizing the psychological crisis state of senior students are 82.51%, 8.19%, and 7.25%, respectively, and the effect of recognizing the psychological crisis state of senior students is unsatisfactory. This is because there is a large amount of noise in the signal of psychological crisis state of higher vocational students, and the method does not process the noise, which produces a certain interference in feature extraction, making the error rate of psychological crisis state recognition of higher vocational students relatively high.

(2) The correct rate, misrecognition rate and refusal rate of BP neural network for recognizing the psychological crisis state of higher vocational students are 83.98%, 8.09% and 6.78%, respectively, and the effect of recognizing the psychological crisis state of higher vocational students has not reached the best. This is because although this method performs noise processing on the psychological crisis state signal of higher vocational students and eliminates the interference of noise, because the BP neural network is a learning algorithm based on the principle of minimum empirical risk, it is prone to the problem of "overfitting" or "underlearning", and the accuracy of psychological crisis state recognition of higher vocational students needs to be further improved.

(3) The correct rate, misrecognition rate and rejection rate of the psychological crisis state recognition of higher vocational students in this paper's method are 93.78%, 3.09% and 2.08%, respectively, and the correct rate of the psychological crisis state recognition of higher vocational students in this paper's method is 11.27% and 9.80% higher than that of the Support Vector Machines and the BP Neural Networks, respectively. This is because the method in this paper first preprocesses the psychological crisis state signals of higher vocational students, extracts better recognition features by using global chaotic bat counting, and introduces the current deep learning algorithms of Res-MLP network to establish a better psychological crisis state recognition model of higher vocational students, which reduces the misrecognition rate and the rejection rate of the psychological crisis state recognition of higher vocational students by neural network, and verifies the method in this paper's Superiority.

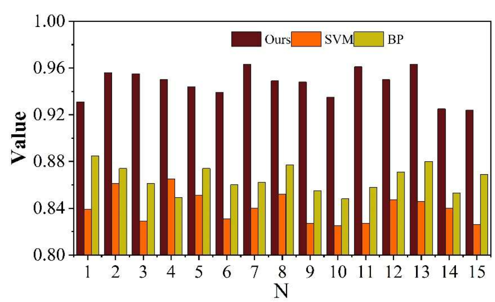

Figure 4: The correct rate of college students' psychological crisis state recognition

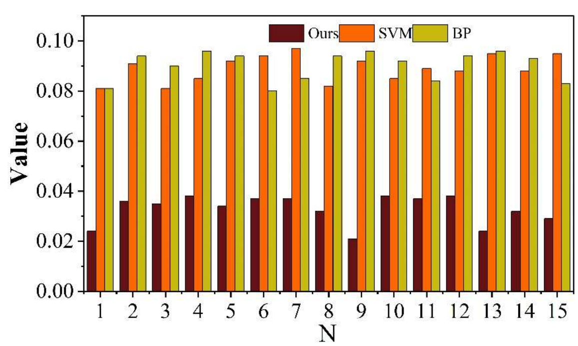

Figure 5: Misidentification rate of college students in psychological crisis state

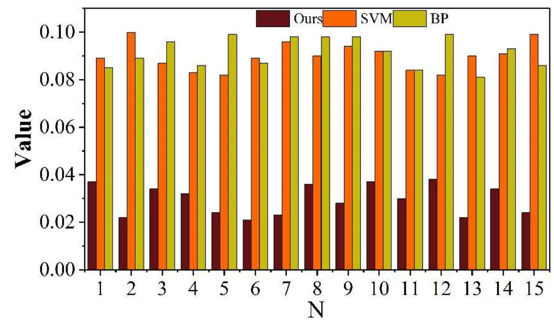

Figure 6: The rejection rate of college students in psychological crisis state

IV. A. 3) Comparison of modeling time for psychological crisis state identification

Due to the continuous expansion of higher vocational education, there are more and more college students, which puts forward higher requirements for the modeling speed of the psychological crisis state recognition method for higher vocational students. The modeling speed is mainly reflected by the modeling time, which mainly includes the training time and testing time of the psychological crisis state recognition of higher vocational students. Statistics on the modeling time of different methods and each simulation experiment of psychological crisis state recognition of higher vocational students are shown in Figure 7. The average value of the modeling time of this paper is 16.92s, while the average value of the modeling time of support vector machine and BP neural network is 31.8s and 29.4s. It can be seen that the method of this paper shortens the modeling time of the recognition of the psychological crisis state of the higher vocational students, accelerates the speed of the recognition of the psychological crisis state of the higher vocational students, and has a higher value of the practical application.

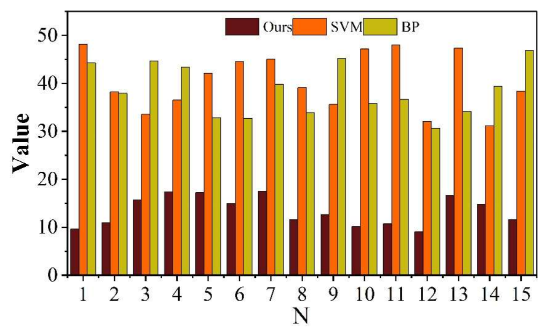

Figure 7: Student psychological crisis state identification modeling time

IV. B. System validation analysis

IV. B. 1) Performance testing

The response time for different concurrency numbers is shown in Figure 8. During performance testing, one should concentrate on evaluating the performance of the system under different concurrent user accesses. In order to simulate real-world usage scenarios, this chapter designs a response time test to verify the system's responsiveness under multiple concurrent user levels and to ensure that the system still runs stably and smoothly under high load. According to the test data in the figure, the response time variation of the system under different concurrency numbers reveals its processing capability and stability. Although the average and maximum response times are significantly longer when the number of concurrency increases, the system still maintains a relatively stable minimum response time under high concurrency, which indicates that the system performs efficiently under low concurrency, with fast processing speeds and short response times, in line with the requirements of daily operation. As the number of users increases, the system's response time increases, but it is still manageable, indicating that the processing capacity is within the expected range. Even at the peak of concurrency, the system maintains a stable minimum response, demonstrating a certain degree of processing toughness and stability. Overall, the system has an expected downward trend in performance when the number of concurrency increases, but the overall performance is stable, especially under high concurrency, which still maintains a certain level, indicating that the system is designed to have better concurrency processing capability and stability. This provides data support for the system in actual deployment, optimization of resource allocation, and expansion strategy, which guarantees the stable operation of the student mental health early warning system under the multi-user scale, and provides reliable services for higher education.

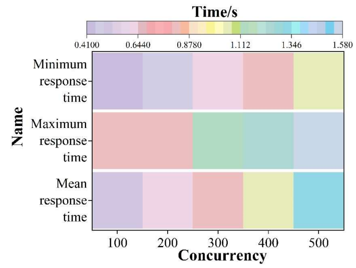

Figure 8: Different concurrent response times

IV. B. 2) Security testing

Security testing is a critical step to ensure that the Student Mental Health Alert System is able to withstand potential threats, protect user data privacy, and maintain service stability. A series of comprehensive measures were taken in the security testing session of this system to comprehensively assess and enhance the security of the system, and the results of the security testing are shown in Table 1. The security test results show that the comprehensive security assessment for the student mental health early warning system using a variety of professional tools (including AWVS, Nessus, and SonarQube) has resulted in the distribution of vulnerabilities and the repair status of the system at different security levels. From the test results, the system performs relatively robustly in terms of security, but there are some areas that need attention. A total of 20 high-risk vulnerabilities were found, which directly threaten system security and may lead to data leakage or illegal intrusion. Thankfully, 20 high-risk vulnerabilities have been successfully resolved, with a resolution rate of 100.00%, indicating that the most serious security issues have been addressed and the system is operating safely. Medium-risk vulnerabilities total 116, which are not as directly fatal as high-risk, but may still affect system functionality or reduce the overall security level. Currently, 100 medium-risk vulnerabilities have been resolved, with a resolution rate of 86.21%, indicating that the system also maintains a relatively high efficiency in dealing with more secondary threats, and the remaining vulnerabilities are resolved using other means after weighing security against other aspects. Under the warning level, the system identified 322 potential risks, which do not directly affect the current security, but suggest that there is room for improvement. 214 warning items have been adopted and resolved, with a resolution rate of 66.46%, which is open to optimization suggestions, and is actively adopted to improve the overall health of the system. To summarize, the Student Mental Health Alert System has demonstrated its positive attitude and effective response to security protection through this security test, especially in dealing with high- and medium-risk vulnerabilities. However, there are still a small number of unresolved vulnerabilities and warnings that need to be continuously tracked and optimized in order to further consolidate the security of the system and ensure the absolute safety of student information and system operations. Future efforts should focus on continuous monitoring of these unresolved issues and continually improving the security resilience of the system through regular security audits and maintenance. Throughout the testing cycle, every security vulnerability found was documented in detail, followed by immediate action to fix it by the author based on the report, and regression testing to ensure that the vulnerability has been completely resolved. This closed-loop security testing process ensured that the student mental health early warning system was fully upgraded in terms of its security performance before deployment, providing a solid guarantee for student mental health information.

Table 1: Safety test results

Test tool	Vulnerability level.	Description	Solved number	Outstanding quantity	Solution Resolution rate
AWVS Nessus SonarQube	High-risk vulnerability	A serious vulnerability that directly leads to system intrusion or data leakage	20	20	100.00%
	Medium vulnerability	A vulnerability that can be exploited to affect the functionality of parts of a system or reduce security	116	100	86.21%
	Warn	Potential risks that do not directly affect safety but suggest improvements	322	214	66.46%

V. Conclusion

In this paper, the acquired research data are normalized and balanced, followed by data feature selection work with the help of global chaotic bat algorithm. The feature data are put into the Res-MLP model as inputs for iterative training and optimization, and the construction of artificial intelligence behavioral model is realized. Synthesizing the above data and model, the multidimensional early warning system for mental health of higher education students is designed. It is found that the system in this paper still shows a relatively stable response time with a value of 1.332s in the case of 500 concurrences, which ensures that the system operates stably under the scale of multi-users and provides reliable services for higher vocational education.

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