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Research Article

Cloud Data System Design for Mental Crisis State Recognition of College Students Based on Machine Learning

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At present, Chinese college students are facing a lot of psychological pressure; whether it is teaching pressure or life pressure, it will have a certain adverse impact on college students' psychological state, and if timely guidance is not provided, it will result in some adverse consequences. Therefore, it is necessary to timely identify the psychological crisis situation of college students, but the existing form of manual identification has high limitations, which cannot obtain the psychological state of students more accurately and efficiently, so it is necessary to optimize and improve with the help of network technology. Cloud computing data system is one of the mature big data systems at present. The combination of cloud computing system and machine learning technology is effectively applied to the field of psychological crisis analysis, which can quickly screen the psychological status of college students and report abnormal data in a timely manner, so as to help college psychological teachers identify the state of college students' psychological crisis and intervene in a timely manner to promote the physical and mental health of students. By applying machine learning technology for the establishment of a cloud computing data system and putting the system into the field of psychological crisis identification of Chinese college students, this study lays a theoretical and practical foundation for preventing students from the psychological crisis.

1. Introduction

The development of cloud computing technology has changed the operation mode of computers, and it can easily meet the needs of the industry and academia for computing and storage. Cloud computing can easily expand the service scope and infrastructure according to user needs and can adapt to the management of the services provided [1]. Therefore, high-performance cloud computing services can not only improve the quality of cloud application services but can also bring more benefits to cloud providers [2]. In addition, the progress of machine learning technology can not only provide good solutions for the needs of multiuser shared hardware resources but can also provide reliable technical support for the realization of many computer technologies [3]. Because cloud computing has innovative resource management, excellent performance isolation services, and low-cost use sources, it has become the best choice for large-scale data-intensive computing applications [4]. At present, many applications need to use special internal servers to run, so it is turning to a cloud computing environment for processing and storing a large amount of data generated by users every day. Data system cloud storage plays an important role in the cloud computing environment, such as healthcare systems, smart homes, or environmental monitors. Therefore, this study applies this technology to the field of psychological crisis analysis of Chinese college students [5]. At present, the psychological crisis of college students has become one of the main problems affecting college teaching, so effective early intervention means for psychological crisis is very important. However, at present, the means of warning students' psychological crisis are relatively single. In most cases, SCL is only used to test the students who have just entered the freshman stage [6]. Therefore, the effective use of new technologies to extract and analyze students' behavior data to determine the realization of early psychological warning is very important to manage students' mental health. This study proposes a student psychological crisis early warning method based on a cloud computing data system [7]. We identify the status of students according to different values of behavior characteristics, so as to judge whether the subject may have a psychological crisis [8]. In the process of selecting personality traits, this study consulted the opinions of student management experts and conducted a binary logistic regression analysis on some traits [9]. Finally, six personality traits, such as family composition, family economy, family relations, class leave, personality characteristics, and failing grades were selected and applied to the modeling decision tree, and the model was qualitatively analyzed according to relevant data by confirming its credibility and reference value [10]. Comparing the test results of several different datasets in the model, it can be seen that the overall prediction accuracy of the model reaches more than 95%, the average recall rate can reach more than 60%, and the F value is stable at more than 70%, which proves that the model has good generalization ability.

2. Related Work

The literature implements a kind of application system architecture focusing on early warning models. The system is based on the Web-based B/S system, the back-end adopts Spring MVC framework, the front-end adopts JSP language, and the database adopts MySQL development [11]. It has key functions such as collecting students' basic information, managing grades, and application approval, and these functions can be used to generate corresponding data so as to finally realize the early warning function for students' psychological crisis and to complete students' management tasks. The literature introduces the multitenant characteristics of the cloud computing environment, optimizes the overall architecture of traditional cloud storage, and then optimizes and improves each component in terms of high performance and high reliability [12]. It mainly includes data index organization, data storage method, data replication mechanism, data confidentiality mechanism, and data positioning mechanism optimization design form. As a part of the early warning of psychological crisis, the discussion was launched, and finally, the internal structure, technical route, and organizational structure of the system were introduced [13]. The literature explains the purpose and background of the system research and construction, combines the real needs of users to analyze the actual application scenarios, and carries out the overall design and detailed system design of the system, including system management module, information collection module, scoring management module, and leave approval module [14]. Compared with the related existing research results, the experimental results prove that the dynamic sample entropy model proposed in this study performs better in identifying individual emotions, has excellent universality and generalization ability, and can establish cognition for cross-individual state recognition [15]. The calculation method realizes the optimization and innovation of emotional EEG pattern recognition and can effectively predict human emotions based on EEG signals [16]. The literature collected the cognitive EEG data of 21 subjects for experimental research. Experimental data show that the proposed method can recognize the target speech through selective auditory attention to the subject and can obtain the highest recognition accuracy [17]. The research results found that the selective auditory attention decoding method based on the LSTM model can achieve high-precision decoding of the auditory attention selected from EEG signals [18].

3. Data System Design Based on Cloud Computing

3.1. Cloud Computing Data Placement Model Design. In the process of selecting the data storage location, we need to consider factors such as the intensity of user data, the indexing time of the data, and the correct loading on the storage node. Based on this point, we first carried out mathematical modeling, which fully considered the abovementioned data factors and described the placement of data in a mathematical form. Subsequently, the placement algorithm is selected to solve the above problems in a targeted manner. The algorithm first considers some factors and then makes the best choice for other factors. Since the load balancing of storage nodes has an impact on cluster strength and data strength, we choose to provide an implementation solution that meets the minimum data retrieval time while satisfying the stability of the storage nodes to load and store data.

We use (S_1, S_2, …,and S_M) to represent the strategy of placing the main data block in cloud storage, and we use $Si \neq 0$ to represent a data block of size Si to be stored on node i, indicating that if $Si = 0$, it means that the node cannot be used to store data blocks.

Subsequently, the retrieval time required to recover the data in the read data request is calculated. Let node p instruct the user to send the required reading to the access point. We assume that the same user always uses the same access point to store and read data. If the data block Si stored in node i is brought to the access point of user p, there may be several different transmission paths. We can calculate the shortest transmission path between access point p and node i. Therefore, the time to transmit a data block of size Si from node i to access point p is as follows:

$$T_{S_i} = \sum_{l \in P_{i,p}} \frac{S_i}{B_{l_s, l_e}}, \quad (1)$$

where l represents the path of P_i and p in the shortest path, B_{ls}, l_e is the bandwidth of path l, and l_s and l_e are the source and destination of link l, respectively. If M different data blocks are sent from M different storage nodes at the access point p, where the total size of the data block M is D, then the total transmission time required is as follows:

$$T_D = \sum_{i=1}^{M} \sum_{l \in P_{i,p}} \frac{S_i}{B_{l_s,l_e}}. \quad (2)$$

The mathematical model is as follows:
Minimize

$$T_D = \sum_{i=1}^{M} \sum_{l \in P_{i,p}} \frac{S_i}{B_{l_s,l_e}}. \quad (3)$$

Subject to

$$\begin{aligned} &\sum_{i=1}^{M} S_i = D, \\ &S_i \geq 0, i = 1, \ldots, M, \\ &S_i \leq S^{\max}, i = 1, \ldots, M, \\ &S_i \leq C_i, i = 1, \ldots, M, \\ &V_i \geq L, i = 1, \ldots, M. \end{aligned} \quad (4)$$

We use V_i to represent the remaining storage load of storage node i, then V_i can be expressed as follows:

$$V_i = \frac{C_i}{A_i}. \quad (5)$$

In formula (5), C_i represents the remaining storage space of node i, A_i represents the total storage space of node i. and L is expressed as follows:

$$L = \max\left\{\frac{C_i - S_i}{A_i}\right\}, i = 1, \ldots M. \quad (6)$$

3.2. Cloud Computing Data Positioning Scheme Design. We set server performance indicators including CPU, memory, IO, and network. Then, we calculate the CPU utilization of node iP_{cpu}^i, as shown in formula (7).

$$P_{cpu}^i = \frac{U_{cpu}^i}{T_{cpu}^i}. \quad (7)$$

Similarly, we calculate the resource utilization of memory and IO separately, and the formula can be expressed as follows:

$$\begin{aligned} P_m^i &= \frac{U_m^i}{T_m^i}, \\ P_{io}^i &= \frac{U_{io}^i}{T_m^i}. \end{aligned} \quad (8)$$

Since the storage node group to be accessed has already been determined, there is no need to compare the creation of the storage node with all storage nodes in the entire system. It is only necessary to compare the creation of storage nodes that store data block S at the same time. Here, we first calculate the average utilization of each collection indicator in the data storage block S of the storage node K_s. The utilization rate of the processor source in this set P_{cpus} is expressed by the following formula, where P_{cpu} is the average utilization rate of the processor resources in the entire system and n is the number of points at the summary point.

$$P_{cpu}^s = \frac{1}{n} \sum_{i \in K_s} P_{cpu}^i. \quad (9)$$

Similarly, the average resource utilization of memory and IO is as follows.

$$\begin{aligned} P_m^s &= \frac{1}{n} \sum_{i \in K_S} P_m^i, \\ P_{io}^s &= \frac{1}{n} \sum_{i \in K_S} P_{io}^i. \end{aligned} \quad (10)$$

Among them, P_m^s is the average usage of the storage node memory in the storage data block S and $\mathrm{P}_{\text{io}}^{\text{s}}$ is the average usage of the IO in the storage node set in the storage data block S. Since we use the network hop count to measure the quality of the network, for different copies of the same data, we can calculate the average hop count L_{net}, and the formula is as follows.

$$P_{net}^s = \frac{1}{n} \sum_{i \in K_S} P_{i,p}. \quad (11)$$

We then calculate the usage rate of each index on each server and the average usage rate of the source code. Then, we classify the set of servers storing S data blocks according to their original storage. It can be divided into five categories, namely, A, B, C, D, and E. Class A indicates that the current server's CPU, memory, and IO resource usage which is lower than that of the average system source usage, and the corresponding indicators and network hop counts are also lower than the average. Type B indicates that one of the indicators such as processor usage, memory usage, IO usage, and network hops is higher than that of the corresponding system value, and C, D, and E can be deduced by analogy.

3.3. Encrypted Storage Design of Cloud Computing Data. With the addition of encrypted storage mechanisms, it will inevitably affect the overall performance of the system. Therefore, we need to implement a secure encryption mechanism as soon as possible when the system performance is affected.

Key stream management involves generating and accessing the key stream. The user key stream generation can be generated in the secure storage module or can be independently set by the user. To prevent encrypted data from being erased due to unintentional changes in the user's key stream, two key streams with the same security level can only be set once. In order to prevent the key stream from leaking, we use a pair of asymmetric key pairs to encrypt and store the key stream. If the user automatically specifies the key stream, then the public key of the nonpeer key pair of the security module must be used to encrypt the key, and then we send them to the security module for storage.

The second module is the data encryption and decryption module, which is mainly used to receive user requests and provide encryption and decryption services. If the receiver of the security module receives the request, the external interface (API) of the data encryption module sends the requested encryption operation to the server, and the encryption operation is responsible for using encryption algorithms to process user data. The data encryption module requests the user's key stream from the key management module through the key manager. The key manager retrieves the database key based on the user information and security level information to verify whether there is an appropriate key stream. If not, it checks whether there is a user-defined secret key. If it is customized, it then saves the ciphertext and decrypt it and return the plaintext. If it is not specified, the key management module will automatically generate the key of the corresponding level, encrypt it, save it, and return it to plain text. After the data encryption and decryption module receive the key stream, it performs data encryption and decryption services.

In addition, we provide optional levels of security encryption for users who use the default key stream. Users can set their own security level according to the characteristics of their own data or can use the default security level of the security module. For users who provide their own key streams, they can provide key streams of different lengths of security modules according to different data to meet changes in security levels. Because the stream user key must be stored in the security module, we use the ID that specifically identifies the user information and the security level that uniquely identifies the user key information to identify the stream that will be streamed to the user. Therefore, the database table must contain internal information such as <key_id, level, key.string>, and the structure of the data table is shown in Table 1.

In Table 1, Key_id represents the current key id, User_id is the user id, and level is the encryption level. Key_length represents the length of the user-defined key. Only one of the two fields, level and Key_length, is valid. If a custom key stream is used, Key_length is valid, otherwise Level is valid. Key_string is a specific key value. We can apply the user id and encryption level according to the key and the value is unique.

3.4. Analysis of Test Results of Cloud Computing Data System Storage Node Balancing Load. In this test, we conducted the same test to realize the design of the cloud storage system and the creation of the MooseFS system in this article. Among them, we use the dd command to periodically write data to the storage system for 2 minutes. Multiple group experiments are conducted, and the stored data after each test are deleted to ensure a consistent test environment. Finally, we use the multiple average results as the final experimental result. Due to a large amount of data, the results are not intuitive enough, so we tested the values for some time and extracted several datasets, that is, the resource utilization of each storage node at a certain time. The loading results of each node of the MooseFS storage system are shown in Figure 1.

Table 1: Key database table structure.

Filed	Type
Key_id	Integer
User_id	Integer
Level	Character
Key_length	Integer
Key_string	String

We use the same test environment and methods to test the load balancing of storage nodes in the cloud storage system designed and implemented in this article and capture the resource usage of each storage node, as shown in Figure 2. It can be seen from the figure that as time goes by, the amount of data in the storage system continues to increase, and the resource usage of each storage node gradually tends to balance.

4. Recognition of Psychological Crisis State Based on Machine Learning

4.1. Theoretical Basis and Model Design of Machine Learning. Through the evaluation and display of the performance of the two models, the four indicators of accuracy, precision, recall, and F value are analyzed, and the most suitable algorithm for this research is selected, as shown in Table 2.

Category information entropy: for example, S is a training instruction sample set, S is composed of s data samples, then S is considered to have a different sample category m, which is defined as $C_i (i = 1,2, \ldots, m)$. If Si is calculated as the number of samples in the category C_i; then, for a given sample dataset, the entropy of category information, that is, the amount of information required for classification can be calculated as follows:

$$I\left(S_1, S_2, \ldots, S_m\right) = -\sum_{i=1}^{m} p_i \log_2 p_i. \quad (12)$$

Conditional information entropy: assuming that attribute A has different values, a total of $\mathrm{v}\{a_1, a_2, \cdots, a\mathrm{v}\}$, attribute A can be used to divide S into v subsets $\{S_1, S_2, \ldots, S_V\}$, suppose S_j has the same value $a_j\,(j = 1, 2, \ldots, v)$ in all samples of A.

Information gain: according to formulas 22 and 23, the information gain obtained by branching on attribute A is as follows:

$$\text{Gain}\,(A) = I\left(S_1, S_2, \ldots, S_m\right) - E\,(A). \quad (13)$$

Split information entropy: in the training sample set S, the samples are classified based on the attribute A value, then the split information entropy calculation formula of A is as follows:

$$SplitI\,(A) = -\sum_{j=1}^{v} p_j \log_2 p_j. \quad (14)$$

4.2. The Design of the Recognition System for the Psychological Crisis State of College Students. The overall design of the

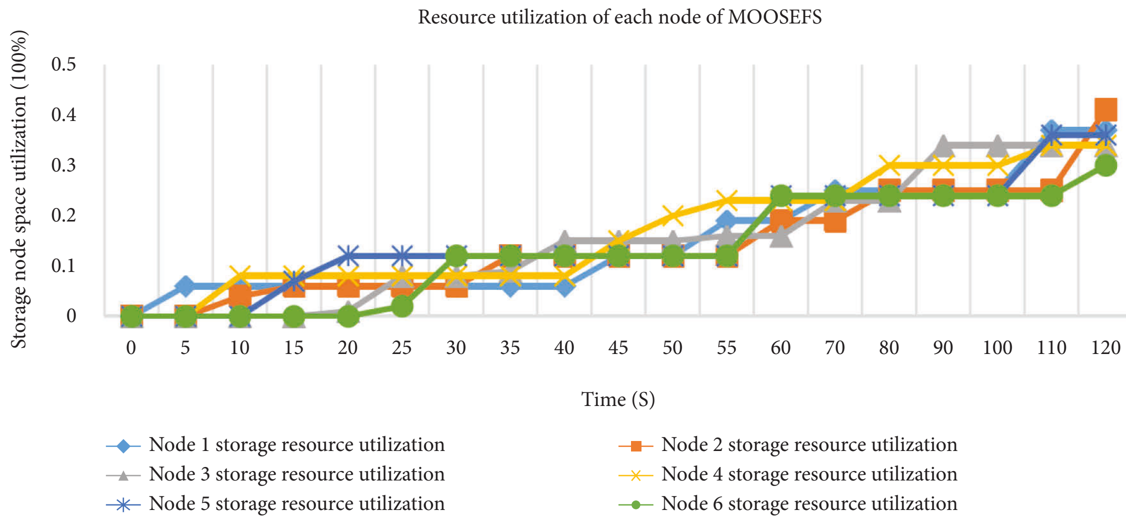

Figure 1: MooseFS resource utilization of each node.

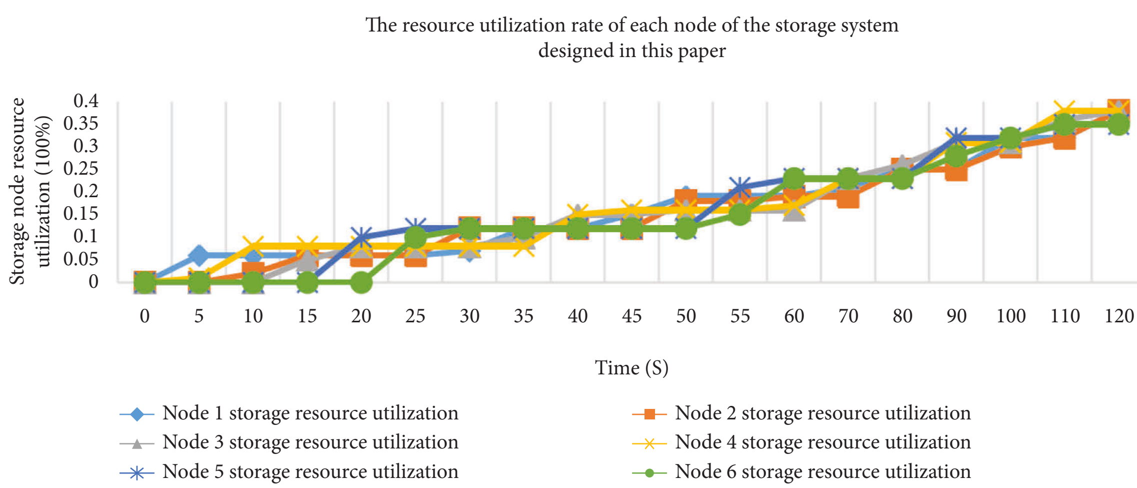

Figure 2: The resource utilization rate of each node of the storage system designed in this study.

Table 2: Algorithm performance evaluation.

Evaluation index	C4.5 (%)	CART (%)
Accuracy	97.3	95.7
Accuracy rate	81.9	66.6
Recall rate	64.7	42.8
F value	72.1	52.3

system follows the principles of code reuse. In the development process of the system, not only the performance of basic functions should be paid attention to, but also the function improvement of the system should be considered, and the fast interface of the node should be kept as much as possible. In places that can be extended, such as placing trigger points in the early update of alert rules, if the model is optimized in the future, the rules set by the system can be updated at the same time to facilitate the update and improvement of the next system.

Principle of intuitive interface. the system is suitable for three different types of users and has a wide range. The purpose of research and development is to promote student management by student managers and classroom teachers. The system is easy to understand and easy to use.

The application system architecture takes the early warning model as the core, adopts the Web-based B/S architecture, and uses the Apache Tomcat server. Database applications can more efficiently separate and store data and can access MySQL databases. The back-end adopts the Spring MVC deployment framework and the main components adopt JSP technology. The overall system architecture is divided into five layers from top to bottom, namely the visual view layer, the control layer, the business logic layer, the data access layer and the data storage layer. The general architecture of the system is shown in Figure 3.

4.3. Analysis of the Recognition Results of the Psychological Crisis State of College Students. In order to test the design of the ETR model learning method based on dynamic entropy to determine the recognition of emotional valence, first, the sliding method is used to obtain dynamic entropy

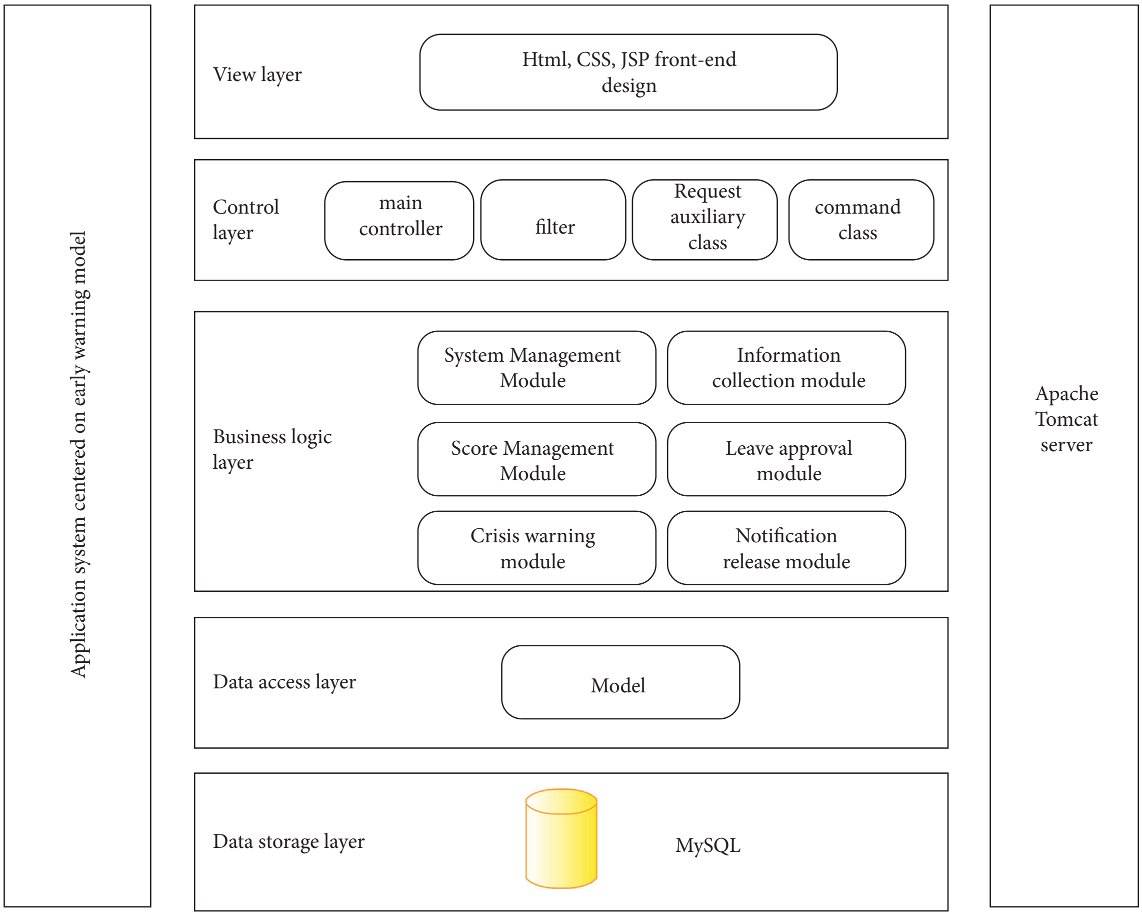

Figure 3: System overall architecture diagram.

component samples from the EEG signal. The EEG data used in the experiment lasted 60 seconds. We use a time window with a duration of 4 seconds, and the duration of each movement of the window is 2 seconds. Therefore, each channel in the EEG time series can capture the entropy patterns in 29 consecutive EEG samples. Figure 4 shows the statistical results of dynamic samples of the EEG signal entropy components of all channels in the 29-hour window, and the subjects are in a negative emotional state.

Subsequently, the correlation t-test was used to test the significance of the EEG entropy characteristics of positive and negative emotions. Figure 5 shows the p value of the entropy result of the dynamic EEG samples of all channels in the 29-hour window of positive and negative emotional states. As shown in Figure 5, the horizontal axis represents the 29-hour window arranged in chronological order, and the vertical axis represents approximately 62 EEG channels. The redder the area, the more significant is the variability of the entropy characteristics of the brain electrical channels corresponding to the time window of the positive and negative sensory states.

Table 3 lists the EEG model learning method based on dynamic entropy to determine the consequences of positive and negative emotion recognition. The experimental result data include the test result standard and definition deviation of 15 subjects. The experimental stage (session order, SesOrd) is the corresponding data of 1, 2, and 3 EEG emotions and the EEG model learning method based on dynamic entropy to obtain the accuracy of individual positive and negative emotion recognition are $82.01\% \pm 13.21\%$ and 82.68, respectively. $\% \pm 16.21\%$ and $82.68\% \pm 19.08\%$. For the EEG data samples collected in these three experiments, the overall accuracy of identifying cross-individual negative and positive emotions is very close. The experimental results show that the EEG model learning method based on dynamic entropy can identify cross individual emotional valence and has good stability.

Table 4 shows the comparison of methods for detecting emotional valence based on EEG signals. Experimental comparison results show that the proposed EEG emotion recognition method based on the dynamic entropy input model shows a better overall recognition rate and generalization performance.

4.4. Work Strategies Based on the Psychological Status of College Students. This study confirms the intermediary role of College Students' basic literacy and personality development in the psychological crisis caused by college students' life pressure and also confirms that college students' core literacy and students' personality advantages should be paid more attention. The university stage is not only an

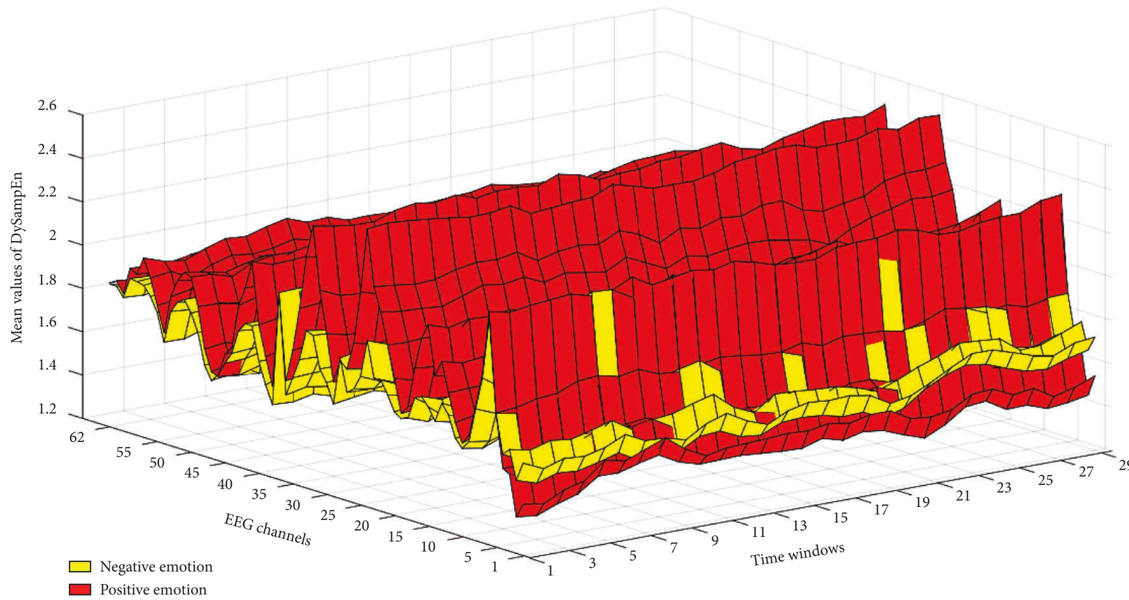

FIGURE 4: The average entropy of the EEG dynamic sample entropy corresponding to each channel in each time window under positive and negative emotional states.

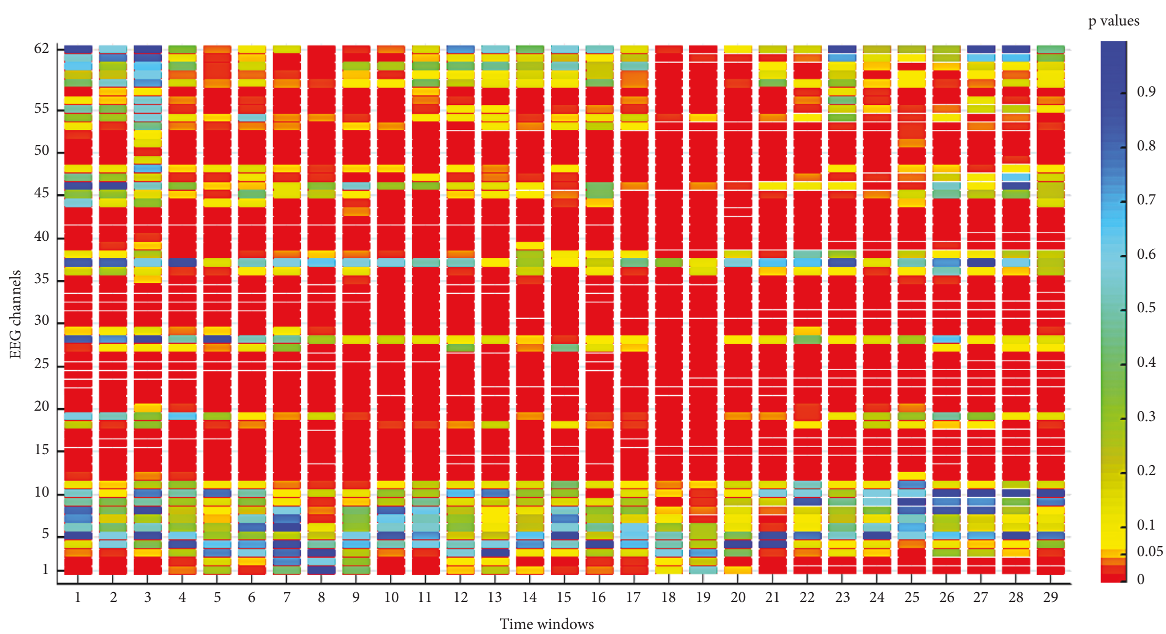

FIGURE 5: The entropy of the EEG dynamic samples corresponding to each channel in each time window is the p value result of the paired sample t-test in the positive and negative emotional states.

TABLE 3: EEG emotion pattern learning method based on dynamic entropy realizes cross individual positive and negative emotion recognition results.

Experimental rounds	Accuracy (%)	Sensitivity (%)	Specificity (%)	Error rate (%)	Number of samples
1	82.01 ± 13.21	82.68 ± 24.93	81.34 ± 20.67	18.00 ± 13.21	150
2	82.68 ± 16.21	86.68 ± 24.68	78.68 ± 31.58	17.34 ± 16.25	150
3	82.68 ± 19.08	80.01 ± 34.65	85.34 ± 27.75	17.34 ± 19.08	150
1, 2, 3	84.65 ± 12.02	85.34 ± 18.88	84.01 ± 23.08	15.34 ± 12.02	450

Table 4: Performance comparison between the research work in this article and existing related emotion recognition research.

Method	Cross individual verification	Result
QTFD and SVM	NO	85.9% (valences, 2 classes)
Statistical, power spectral and HOC features, and SVM	NO	58.9% (valences, 3 classes)
Entropy, PS features, LSP, KNN, SVM, and MLP	NO	63.48% (valences, 3 classes)
DE, DASM, RASM, and SVM	NO	83.98% (3 classes)
DE and SVM	Yes	60.94% (3 classes)
ApEn, PerEn, ShEn, and SVM	Yes	83.34% (2 classes)
DySampEns and SVM	Yes	85.12% (2 classes) 64.16% (3 classes)

important moment for teenagers' physical and mental development but also a key moment for cultivating the characteristics and advantages of basic values and health care quality. Based on the theory of students' basic core quality and personality advantages, this study puts forward the following suggestions by studying the relationship between them and students' psychological crisis

First, we cultivate students' positive psychological quality and improve their psychological pressure resistance. While improving students' core literacy and culture, we strive to improve their own core competitiveness from all angles and fields, especially focusing on cultivating psychological literacy, so as to make them have excellent psychological quality, and to prevent the occurrence of psychological crisis.

Second, we carry forward the character advantages and enhance the students' individual judgment and will quality. The development and cultivation of personality advantage is not only an important factor in forming a good personality but it also an important factor for the premise of cultivating faith quality and strong will. College students' activity areas are mainly dormitories and classrooms. Therefore, it is necessary for college educators to create a positive educational environment on campus, promote students' all-round progress, shape students' behavior and moral standards, and affect students to establish good psychological quality.

Third, due to the differences between colleges and universities, different students have different growth environments and life experiences, so their psychological states and learning level are different, and the psychological attitudes of students at different training levels are also slightly different. Based on the analysis results, in view of the differences in the psychological crisis of students in provincial colleges, vocational colleges, and private colleges, individualized education for students' basic literacy and personality advantages should be implemented. Colleges and universities in the province should pay attention to promoting students' cultural accumulation and improving students' aesthetic quality. In the field of students' technical training, provincial colleges and universities need to pay attention to professional knowledge, skills, and innovative consciousness. According to the characteristics of colleges and universities, such as literature and history, science and technology, electronics, architecture, petroleum, and other fields, it aims to cultivate students with unique skills in this field.

Fourth, various power systems need to be fully developed and improved. If an individual encounters pressure, makes psychological actions and falls into a psychological crisis, then the individual cannot respond to thinking, reasoning and decision-making in time. Therefore, it is necessary to deal with the psychological crisis with the help of external forces. Nowadays, most students of crisis prevention and psychological intervention tend to work in the school system, thus ignoring the impact on the social environment and family growth environment. The intervention of students' psychological crisis not only needs to improve the system but also needs to have various support and defense. In a psychological crisis, school intervention is necessary, and the family environment must be effectively used. The positive synergy between school education and social culture interferes with the four levels of individual family school society in terms of a psychological crisis. At the same time, social networks should have a sense of social responsibility when reporting students' psychological crisis events, avoid exaggerating and using negative public opinion, and enable the public to pay attention, respect, and accept individuals or groups.

5. Conclusion

The purpose of this study is to analyze the student data that student managers often come into contact with in their daily work, so as to explore the hidden laws behind the data, so as to better identify the psychological dynamics of students and provide early warning for possible psychological crisis problems. First of all, this study sorted out and studied the research materials in related fields in recent years, and carried out a special study on the identification of psychological crisis states. The results show that the cloud computing system based on the data decision tree algorithm is most suitable for this research and it fully meets the requirements. Based on this point, this article has determined the scope of studying student data through field surveys, collected available data using questionnaire surveys, and established a basic dataset of students. Based on the basic common sense, relevant work experience and suggestions of the student management experts, the attributes of nonobvious research importance are screened, and the binary logistic regression analysis is performed on the whitened data matrix of the remaining quality attributes, and 6 attributes obtained retrospectively are highly related to psychological crisis. The characteristic attributes of sex are personality characteristics, family composition, family economics, family relations, leave type, and status of school leave. The abovementioned six characteristic attributes are used to construct the main psychological crisis early warning system. Through experiments to test the performance of the two classic judgment tree algorithms C4.5 and CART in decision-making, comprehensively considering the precision, accuracy, and recall rate, this study finally chooses to use C4.5 psychological crisis as the early warning decision tree model application. Through experiments, 14 rules with positive warning results are obtained to describe the model. Through effective scientific explanation and quantitative analysis of the measured results, the reference value and comprehensive ability of the model can be scientifically demonstrated and proved.

Data Availability

The data supporting the current study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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