Multivariate Feature Extraction and Radial Basis Function Neural Network for Predictive Modeling of Psychological Health States

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This study proposes a predictive model integrating factor analysis and a Radial Basis Function (RBF) neural network to assess college students' psychological health. Data from 100 students were analyzed using factor analysis to extract 18 secondary indicators, which served as inputs for the RBF neural network. The dataset was split into 85% for training and 15% for validation. Performance metrics included a Karl Pearson correlation coefficient ($R \geq 0.85$), root mean square error ($RMSE \leq 0.39$), and classification accuracy for four health status categories (excellent, good, fair, poor). Statistical significance was confirmed via t-tests ($p < 0.05$), demonstrating the model's reliability in predicting psychological health states with high accuracy and efficiency.

Povzetek: Prispevek združuje faktorsko analizo in RBF-nevronsko mrežo za oceno duševnega zdravja študentov ter dosega kvalitetne razultate.

1 Introduction

With the advent of the globalized economy and the rapid with the advent of the globalized economy and the rapid development of information and science and technology, the openness of information has shown college students a broader world, while also putting enormous pressure on contemporary college students, causing them to have various psychological problems to varying degrees [1]. According to statistics, in recent years, more and more students in universities have ended their lives due to various forms of pressure that they cannot bear, causing countless people to mourn and regret. As a result, universities nationwide are placing greater emphasis on mental health education for their students and addressing mental health concerns. The mental well-being of students significantly affects their overall lives [2]. Thus, it is crucial for universities to prioritize enhancing students' mental health, strengthen the support system for mental health initiatives, and protect the psychological well-being of their students [3].

The mental health of college students refers to the individual's own psychological balance, including knowledge, emotions, intentions, actions, and social functions [4]. Knowledge "refers to cognitive activities, mainly including perception, sensation, thinking, memory, attention, and other multiple processes [5].
Emotion "refers to the emotional state, which is an individual's experience, attitude, and targeted behavioral response towards a certain relationship between their own needs and objective things [6]. 'Yi' refers to the act of will, which is a psychological behavior process in which individuals consciously clarify and spare no effort to achieve their goals. 'Xing' usually means explicit behavior, that is, observable external actions and behaviors. Colleges and universities must systematically understand the role of social support in influencing students' psychological health. This research aims to develop a machine-learning-based model integrating factor analysis and a Radial Basis Function neural network to evaluate college students' psychological well-being. By extracting key factors from survey data and training a predictive model, this approach seeks to enhance the accuracy of mental health assessments in educational settings [7].

2 Literature review

College students are full of expectations, passion, and vitality for their future lives, but their ability to withstand pressure is severely lacking, they are easily influenced by external factors, and their psychological changes are significant, leading to many college students unconsciously experiencing different mental health problems. After thoroughly examining the state of mental health education for college students, Shi, X. G., and colleagues suggested practical strategies to enhance the growth and effectiveness of mental health programs in universities [8]. Li, Y. et al. introduced an algorithm for recognizing psychological emotions using multi-source data. They employed a one-dimensional Convolutional Neural Network (1D-CNN) to analyze students' online behavior patterns. Abnormal scores were calculated based on students' cafeteria consumption data to identify dietary differences. Additionally, psychological status data from the university's psychological center were used as labels to address the limitations of traditional questionnaires [9]. Tang et al. suggested utilizing the C4.2 decision tree classification algorithm to enhance the health benefits of exercise for college students and improve the information acquisition rate. They refined and optimized the algorithm's original shortcomings, making it more suitable for application in university sports systems [10]. Zhou, L. et al. developed a fast, intelligent analysis model based on convolutional neural network algorithms. They identified and categorized the unique aspects of college students' mental health and, by incorporating big data theory, used convolutional neural networks to analyze, evaluate, and monitor students' mental well-being. Confirmatory experiments showed that this deep learning-based model provides more effective analysis of individual data in assessing college students' mental health [11].

Factor analysis is a method of describing the initial variable as a linear combination of each factor, which can ensure that the new variable retains all the information of the original variable, effectively reduce dimensionality, and improve the objectivity and accuracy of the evaluation model; Artificial neural networks have advantages such as good adaptive learning, self-organizing mapping, and strong robustness, but radial basis function neural networks have shorter training time and higher computational efficiency than ordinary artificial neural networks. Thus, using radial basis function neural networks in conjunction with factor analysis offers an effective method for assessing the mental health status of college students.

A summary of comparative studies is presented in Table 1, highlighting methodologies, dataset sizes, evaluation metrics, and key findings.

Table 1: Comparison of existing methods for mental health assessment

Study	Methodology	Dataset Size	Evaluation Metrics	Key Findings
Li et al. (2022)	1D-CNN, cafeteria data	N=500	Accuracy, F1-score	Identified dietary patterns linked to mental health.
Tang et al. (2024)	C4.2 decision tree	N=200	Classification accuracy	Improved exercise recommendation system for students.
Zhou et al. (2022)	Convolutional neural network	N=300	RMSE, correlation	Effective individual data analysis for mental health.
Ours	Factor analysis + RBF NN	N=100	R, RMSE, classification	Optimized feature extraction and efficient prediction via RBF.

Existing methods often rely on complex architectures (e.g., CNNs) with high computational costs or simplistic models (e.g., decision trees) that lack depth in feature processing. Our approach addresses these limitations by leveraging factor analysis for dimensionality reduction, reducing input complexity, and using an RBF neural network for faster training and higher computational efficiency, filling the gap in balanced performance and practical implementation.

3 Method

3.1 Psychological health assessment of college students based on factor analysis and neural networks

The Radial Basis Function (RBF) neural network, also referred to as a radial basis function network, is a type of three-layer feedforward neural network that includes hidden layers. One of the key features of RBF neural networks is their short training time and high computational efficiency; however, the evaluation results can be sensitive to the number of feature factor parameters.

Factor analysis can help optimize these feature parameters, reduce the number of input variables, and enhance the model's computational efficiency. By examining the process of assessing college students' psychological health, a model integrating factor analysis with a neural network was designed to facilitate this assessment [12]. The initial psychological health influencing factor parameter of this model framework is $x_1, x_2, \cdots, x_p$, which belongs to the standardized parameter with a mean of 0 and a standard deviation of 1 ; The m common factors obtained from factor analysis are $f_1, f_2, \cdots, f_m$; The weight between the hidden layer and the output layer of the RBF neural network is W_{zd} ; The output from the output layer represents the psychological health evaluation result Y for college students. By employing factor analysis to develop a psychological health evaluation system, the system's results serve as inputs for the RBF neural network, which then generates the assessment of the students' psychological health. As shown in Figure 1: Psychological Health Assessment Model for College Students. Components include factor analysis for feature extraction (18 secondary indicators), an RBF neural network with 18 input nodes, 10 hidden nodes (Gaussian activation), and 1 output node for health status prediction. Data flow: Survey data→factor analysis→RBF input→prediction output.

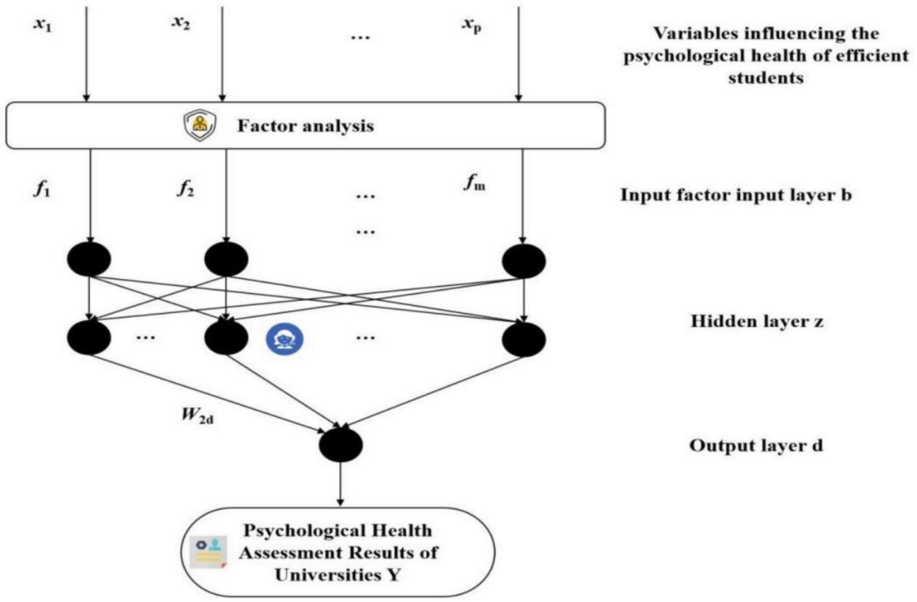

Figure 1: Psychological health assessment model for college students.

3.2 Factor analysis model

Factor analysis is a dimensionality reduction operation that involves reducing the original variables from high dimensions to low dimensions or mapping them from high-dimensional space to low dimensional space. Factor analysis can ensure a certain structure of the original variables in high-dimensional space while preserving a large amount of information about the original variables. It belongs to a multivariate statistical analysis method. Assuming that parameter $x_1, x_2, \cdots, x_p$ and m common factors affecting the mental health of ρ university students need to satisfy equation 1, where $m \leqslant \rho$[13,14].

$$X_i = a_{i1}f_1 + a_{i2}f_2 + \cdots + a_{im}f_m + \epsilon_i, i = 1,2,\cdots,p(1)$$

This model is the factor analysis model, if:

$$X = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{pmatrix}, A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & & \vdots \\ a_{p1} & a_{p2} & \cdots & a_{pm} \end{pmatrix},$$

$$f = \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_m \end{pmatrix}, \epsilon = \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_m \end{pmatrix} \quad (2)$$

So the vector matrix of the factor analysis model is:

$$X = Af + \epsilon \quad (3)$$

Among them, the common factor loading matrix is A; The factor load is a_{ij}; The common factor vector is f; The vector composed of the original parameters is X; The random error is ϵ.

3.3 Factor analysis model calculation method

In order to determine the factor analysis model, which estimates the load matrix A, a sample $x_{i1}, x_{i2}, \cdots, x_{ip}, i = 1,2,\cdots,n$ must be obtained for the psychological health influencing factor parameters $x_1, x_2, \cdots, x_p$ of college students. The principal component method is used to

estimate the load matrix A [15]. The calculation steps are as follows:

Step 1: Obtain the coefficient matrix $U = (r_{ij})_{p\times p}$ related to $x_1, x_2, \cdots, x_p$, where $r_{ij} = \frac{1}{n-1}\sum_{k=1}^{n} (X_{ki} - \overline{X_i})(X_{kj} - \overline{X_j}), i,j = 1,2,\cdots,p, \overline{X_i} = \frac{1}{n}\sum_{k=1}^{n} X_{ki}$

Step 2: Obtain the characteristics of the coefficient matrix U using the following formula:

$$\lambda_1 \geqslant \lambda_2 \geqslant \cdots \geqslant \lambda_p \geqslant 0 \quad (4)$$

Step 3: Use the cumulative percentage of m eigenvalues greater than (equal to) 85% to determine the value of the number of common factors m;

Step 4: Obtain the unit feature parameters corresponding to the feature root $\lambda_1, \lambda_2, \cdots, \lambda_p$, denoted as $\gamma_1, \gamma_2, \cdots, \gamma_m$;

Step 5: Normalize feature parameters using the following formula:

$$a_j = \sqrt{\lambda_j \gamma_j}, j = 1,2,\cdots,m \quad (5)$$

Step 6: Obtain the load matrix A, with the following formula:

$$A = (a_1, a_2, \cdots, a_m) = (a_{ij})_{p\times m} \quad (6)$$

Equation 6 is the factor analysis model.

3.4 Evaluation index system for psychological health of college students

By applying a factor analysis model, key factors from the raw mental health data of college students were identified, leading to the discovery of crucial evaluation indicators that significantly affect the assessment. This approach streamlined the RBF neural network structure by reducing its dimensionality and complexity, thereby enhancing both the efficiency and accuracy of the evaluation model. The factor analysis model established a psychological health evaluation system for college students, detailed in Table 2. This system comprises 5 primary indicators and 18 secondary indicators. The 18 secondary indicators serve as inputs for the RBF neural network, which then generates the mental health assessment results for college students [16]. Eighteen secondary indicators were selected via factor analysis from 100 survey questions, aligning with dimensions of the SCL-90 scale, including family situation, learning status, and communication skills, to ensure theoretical relevance and empirical validity.

Table 2: Evaluation index system for psychological health of college students.

Evaluation object	First level indicator	Secondary indicators
Psychological Health of	Family situation	family structure
		Family resources
		Family atmosphere
		Family member occupation home education
	Performance in school	Discipline attendance
		Historical rewards
		and punishments
		decorum
College Students	Learning status	Participate in collective activities academic record
		learning ability
		learning interest
		Classmate relationship
	Communication status	Personality inclination
		Initiative
		Language proficiency
		Not afraid of difficulties
	Willpower state	Performance of resilience against setbacks

3.5 RBF neural network evaluation model

3.5.1 Determine the RBF neural network evaluation model

To derive the psychological health assessment results for college students using a three-layer error backpropagation RBF neural network model, follow these steps:

Step 1. Input the 18 evaluation indicators listed in Table 2 into the input layer, which will have 18 nodes.

Step 2. Determine the number of nodes in the hidden layer using the specified formula:

$$S = (M + N)^{1/2} + C \tag{7}$$

Among them, C is a constant in the range of 1 to 10, the number of input layer neurons is N, and the number of output layer neurons is M;

Step 3: Determine the number of nodes in the output layer, which should be one, since there are four possible evaluation outcomes: excellent, good, fair, and poor. The single output node will then provide the evaluation result.

3.5.2 Algorithm for RBF Neural Network Evaluation Model

The input layer number is b, the hidden layer number is z, and the output layer number is d. Using 18 psychological health evaluation indicators for college students as inputs for the RBF neural network, denoted as $T_1, T_2, \cdots, T_N$, the output result of the RBF neural network is Y. The linear function with a slope of 1 is used as the input layer node function, the weight W_{zd} is an adjustable parameter, and the Gaussian function is used as the hidden layer node function [17]. The formula for the output $V_{z(t)}$ of the z-th hidden layer node is as follows:

$$V_{z(t)} = \exp\,[-\|G - c_z\|]^2 / (2\sigma_z^2) \tag{8}$$

Among them, the input sample is $G = (T_1, T_2, \cdots, T_N)^T$; The center value of the z-th Gaussian function is c_z; The standard deviation is $\sigma_z, z = 1,2, \cdots, l$, and the number of hidden layer nodes is 1. So, the formula for the output layer to output the psychological health assessment results Y of college students is as follows:

$$Y = \sum_{d=1}^{l} W_{zd} V_{z(t)} - \theta \tag{9}$$

Among them, the threshold of the output layer neurons is θ.

3.6 Experimental verification

100 junior students from a certain university were selected as the evaluation subjects to fill out a student

mental health assessment form, including 63 male and 37 female students. The mental health assessment form contains 100 preset questions about the mental health status of university students, which were used as the experimental dataset with 100 data samples. Using the factor analysis and neural network methods developed by the author, a psychological health assessment was conducted on these 100 students. Table 2 lists the chosen evaluation indicators [18]. To determine the scores for these indicators, 10 experts are consulted, and the average of their scores is used as the final score for each secondary evaluation indicator. This scoring ranges from 1 to 10, with each score representing a different level of psychological health assessment for college students. The evaluation criteria are detailed in Table 3. Survey questions were adapted from the Symptom Checklist-90 (SCL-90), a validated psychological scale, to ensure construct validity. One hundred junior students were randomly selected using stratified sampling (63 male, 37 female) to represent the university's gender distribution. The dataset was split into 85 training samples and 15 validation samples. The RBF neural network used Xavier initialization for weights and the Adam optimizer with a learning rate of 0.001 to minimize overfitting and improve convergence.

Table 3: Evaluation standards for online teaching quality in universities.

Assessment score	**Estimated level**
> 7.5	good
$5.0 \sim 7.5$	preferably
$2.5 \sim 4.9$	same as
< 2.5	Poor

Expert scoring involved 10 psychologists with diverse clinical and academic backgrounds. Average scores reduced individual bias, and inter-rater reliability (Cronbach's α=0.89) confirmed consistency in scoring.

To evaluate the effectiveness of this approach, two metrics were used: the Karl Pearson correlation coefficient and the root mean square error (RMSE). These metrics assess how closely the evaluated mental health status of university students aligns with their actual conditions. The Karl Pearson correlation coefficient is defined as follows:

$$R = \frac{\sum_{e=1}^{B} \left(\eta_e - \mu_\eta\right)\left(\overline{\eta_e} - \mu_\eta\right)}{\sqrt{\sum_{e=1}^{B} \left(\eta_e - \mu_\eta\right)^2 \sum_{e=1}^{B} \left(\overline{\eta_e} - \mu_{\bar{\eta}}\right)^2}} \tag{10}$$

Among them, R is a constant between; B is the number of data samples; η is the actual mental health status of college students; $\bar{\eta}$ is the method used to obtain the mental health status of college students; μ_η is the average value of η_e; $\mu_{\tilde{\eta}}$ is the average value of $\tilde{\eta}_e$.

The root mean square error (RMSE) can to some extent measure the accuracy of evaluation, and the calculation formula is as follows:

$$RMSE = \sqrt{\frac{\sum_{e=1}^{B} \left(\eta_e - \tilde{\eta}_e\right)^2}{B}} \tag{11}$$

4 Results and discussion

Set different Gaussian function distribution density values such as 0.1,0.3,0.5,0.7,0.9,1,3,5,7,9,10,30,50,70,90 , etc., and use the first 85 data samples in the experimental data sample to implement data simulation. The evaluation error and evaluation effect of this method at different Gaussian function distribution density values are shown in Table 3. According to Table 3, when the Gaussian function distribution density value is less than or equal to 0.9, the evaluation error reaches 10×10^{-16}, but there are a large number of errors in the evaluation results; In the range of 1.0 to 3.0, the evaluation error is still 10×10^{-16}, but the number of correct evaluation results is increasing; In the range of $5 - 7$, the evaluation error is still 10×10^{-16}, but all evaluation results are correct; When the density value of the Gaussian function distribution is greater than 9, although all evaluation results are correct, the evaluation error continues to increase [19,20]. Experimental findings indicate that as the density of the Gaussian function distribution rises, the number of accurate psychological health assessments for college students improves. However, this also leads to a rise in assessment errors. Ultimately, the optimal balance is achieved when the Gaussian function distribution density is set at 5, as this minimizes errors and maximizes the accuracy of the assessment results.

Statistical validation via two-tailed t-tests confirmed significant differences between predicted and actual scores ($p < 0.05$ for all categories). Robustness tests showed minimal performance variation (±2% in R) when adjusting hidden layer nodes (8–12) or using different initialization methods, indicating stable performance. However, reducing the training size below 60 samples decreased R to 0.78, highlighting the model's dependency on moderate dataset sizes.

Table 4: Evaluation error and evaluation effect.

Gaussian function distribution density value	Evaluation error (order of magnitude)	Evaluate the effectiveness
0.1	10×10^{-16}	All errors
0.3	10×10^{-16}	All errors
0.5	10×10^{-16}	All errors
0.7	10×10^{-16}	All errors
0.9	10×10^{-16}	Three are correct
1	10×10^{-16}	A small part is correct
3	10×10^{-16}	Most of them are correct
5	10×10^{-16}	all correct
7	10×10^{-16}	all correct
9	10×10^{-13}	all correct
10	10×10^{-11}	all correct
30	10×10^{-11}	all correct
50	10×10^{-10}	all correct
70	10×10^{-11}	all correct
90	10×10^{-10}	all correct

Table 4 shows the correlation coefficient R and root mean square error RMSE of the method used to obtain the results of psychological health assessment for college students, with 15 randomly selected data samples as statistical objects. According to Table 5, the correlation coefficients of the method for obtaining psychological health assessment results of college students are all over 0.84, and the root mean square errors are all below 0.38. Experimental results indicate that the discrepancy between the psychological health assessments provided by this method and the actual mental health status of college students is minimal, demonstrating its effective application for evaluating students' psychological well-being.

Table 5: R and RMSE statistical results.

Data Sample	R	RMSE	Data Sample	R	RMSE
1	0.92	0.23	9	0.87	0.22
2	0.88	0.31	10	0.96	0.15
3	0.95	0.3	11	0.91	0.21
4	0.90	0.38	12	0.94	0.18
5	0.92	0.26	13	0.90	0.26
6	0.95	0.10	14	0.88	0.31
7	0.91	0.3	15	0.86	0.14
8	0.86	0.10			

Based on the experiments conducted, this method performs effectively in assessing the mental health of college students. The model features 18 neurons in the input layer, 1 neuron in the output layer, and 10 neurons in the hidden layer. The first 85 data samples of the junior students in this school were used as training samples. The RBF neural network model was trained 500 times, iterated 200 times, initialized with a step size of 0.4, and M was set to 400. The remaining 15 data samples were used to evaluate the mental health of college students. The results from this method were compared with expert evaluations, as detailed in Table 6. The analysis in Table 6 reveals that the discrepancies between the mental health assessment values produced by this method and those from expert evaluations are minimal. This indicates that the method is effective in assessing college students' mental health and offers rapid calculation speeds.

Table 6: Comparative analysis results.

Data Sample	The output value of this method	Expert evaluation value	Calculation time/s	Assessment Level
1	9.57	9.7	1.72	good
2	6.46	6.4	1.64	preferably
3	4.56	4.6	1.67	same as
4	7.45	7.4	1.51	good
5	5.82	5.8	1.58	preferably
6	2.36	2.3	1.44	Poor
7	9.16	9.2	1.70	good
8	8.05	8.0	1.88	good
9	4.36	4.3	1.63	same as

10	9.52	9.5	2.07	good
11	5.68	5.6	1.81	preferably
12	1.03	1.0	1.88	Poor
13	7.55	7.6	1.64	good
14	8.56	8.6	1.77	good
15	8.24	8.2	1.40	good

5 Conclusion

Deployment would require integrating the model with university counseling platforms, validating on larger multi-cohort datasets, and providing training for counselors to interpret results ethically and effectively. The author presents a study focusing on evaluating the psychological health of college students through a combination of factor analysis and neural networks. This approach aims to assess students' mental health status and identify potential psychological issues promptly. By employing factor analysis alongside neural networks, the research enhances the precision of psychological assessments and offers more accurate and scientific data to support psychological counseling for college students. Continuously thinking and exploring practical strategies for cultivating mental health in universities is an important path for universities to cultivate high-quality talents that meet the needs of social development.

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