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Research Article

Research on Teaching Quality Evaluation Model of Higher Education Teachers Based on BP Neural Network and Random Matrix

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Improving teaching quality is the first task of higher education, and evaluating teaching quality is an effective measure to improve teaching quality. Combining the advantages of BP neural network and random matrix algorithm, the teaching quality evaluation model of higher education teachers is established. In this paper, the improved BP neural network and the random matrix structure are used to normalize the indicators, evaluate the teaching indicators, and build the teacher teaching quality evaluation system model. Through experimental design, the training data set is input into the model for training. In the training process, the increase and decrease ratio of learning rate, momentum term, and other parameters are adjusted to improve the prediction accuracy and convergence speed of the model. Iteration times, training time, MSE, and prediction accuracy were taken as performance comparison indexes of the model. Experiments show that the model solves the shortcomings of the existing teaching quality evaluation methods and models to a certain extent, and improves the accuracy of evaluation prediction. When the number of iterations is 133, the prediction accuracy is as high as 94.9%, which verifies the effectiveness of the model in the evaluation of teaching quality in colleges and universities. Finally, the evaluation index system of teacher teaching quality is comprehensively analyzed, and the results prove that the evaluation model of teacher teaching quality of A university is suitable for the situation of the school, can highlight the guidance, and is scientific and measurable of evaluation.

1. Introduction

The competition in the 21st century is about the quality of talents, and the challenges of all countries in the world are also about the quality of talents. Colleges and universities are important training bases for senior talents, and the quality of teaching is the foundation of colleges and universities. Teaching quality is related to not only the survival and development of a university, but also the concentrated performance of the overall competitiveness of a university. Improving teaching quality is an eternal theme of education [1]. It is one of the main problems faced by colleges and universities.

The teaching quality of higher education should be improved, and the evaluation of teaching quality is an effective measure to improve teaching quality [2]. At present, there are many problems in the evaluation of teaching quality, such as single- and one-sided evaluation standards, evaluation focusing on results rather than process, and evaluation focusing on quantitative analysis rather than qualitative judgment. It is of great significance to establish a scientific and comprehensive teaching quality evaluation system for teachers to strengthen the efficiency of teaching management, improve teaching quality, enhance teaching research, and cultivate high-quality talents. Therefore, it is necessary to establish a rigorous and scientific evaluation system of higher education teaching quality and constantly improve the construction of teachers.

The establishment of teaching quality evaluation model is influenced by many factors, which is a very complicated process [3]. In this paper, BP neural network and random matrix algorithm are combined to improve the BP neural network. The improved BP neural network and random matrix can be used in teaching quality evaluation to eliminate basic differences and make the evaluation results more fair and reliable.

2. Related Discussion

Under the background of continuous progress of information technology, many Chinese and foreign educators have carried out research and practice in teaching quality evaluation system [4]. Many scholars have proposed various teaching evaluation models. For example, Chen et al. used fuzzy algorithm to establish a teaching quality evaluation system. The system can not only evaluate each module in the teaching process and the personality of the students, but also evaluate the whole. During the teaching process, regular self-assessment can also be synchronized according to the actual situation of the students [5]. Yuan and Li compiled and published the book School Education Evaluation. They mainly use analytic hierarchy process (AHP) for quantitative evaluation [6]. Zhu constructed a set of teaching quality monitoring system based on the concept of "people-oriented, three-dimensional integration," in which "people-oriented" mainly refers to teachers and students, while "three-dimensional" refers to the top-level dimension (school), the middle dimension (second-level colleges), and the basic dimension (teachers) [7]. Filor, Seamus adopted mathematical fuzzy analytic hierarchy process and introduced diversified evaluation methods to change the supervision function and solve the existing problems in teaching quality evaluation [8]. In the literature, Hou designed the evaluation process of mixed teaching mode, which has achieved good results in practical application [9].

The teaching quality evaluation of higher education is a nonlinear classification problem, and its results are affected by the interaction of many factors. Therefore, the most basic factors which can directly reflect the teaching quality should be selected as the evaluation content when the teaching quality evaluation system is established. However, there are some differences in the content and methods of evaluation due to a different understanding and emphasis on teaching quality [10]. Kim adopted BP neural network and related theories to formulate the evaluation index system, constructed an effective computer graphics teaching quality evaluation model, and used this model to evaluate the actual teaching situation of relevant courses [11]. Wenwen proposed the optimized BP model, which has a broad application prospect in teaching evaluation of higher education [12]. Xu and Lang combined the analytic hierarchy process (AHP) and neural network, combined the advantages and characteristics of both, added the screening process in the evaluation, and finally obtained the AHP-BPNN evaluation model [13]. Schneider combined the PSO algorithm with the neural network, used the PSO algorithm to optimize the neural network, and found the global optimal evaluation parameters [14].

To sum up, algorithms such as expert evaluation method, fuzzy comprehensive evaluation method, and neural network model method have been applied in the construction of higher education teachers' teaching quality evaluation system. However, due to the complexity of teaching quality evaluation, the accuracy of evaluation results is low. With the continuous popularization of the Internet, this paper uses the improved BP neural network and random matrix for the teaching quality evaluation model of higher education teachers by virtue of the intelligent advantages of the Internet and based on the advantages of BP neural network and random matrix.

3. Model Construction

In order to design a scientific and comprehensive teacher's teaching quality evaluation system, this paper constructs a teacher's teaching quality evaluation model from four aspects: overall module design, normalization of evaluation indicators, BP neural network and random matrix evaluation model, and evaluation of teaching effect.

3.1. Overall Module Design. Demand analysis is the purpose and basis of software design and development, in order to meet the basic needs of evaluation subjects in the teaching quality evaluation model of teachers [15]. According to the functional requirements of the model, it should meet the following five basic functions, including system management, teaching evaluation, basic data management, teacher evaluation results management, and evaluation model research and evaluation. The functional structure of the model is shown in Figure 1.

The main module functions are as follows:

(1) Function description of the user login module: It is mainly responsible for the management and allocation of users' permissions. The main function is the user login, the user login and password must match, the user login and role should match, for the user input corresponding prompt, but the prompt cannot be accurate to the user name and password error prompt, that is, to give a relatively fuzzy error prompt information [16].

(2) The function description of the user management module: It includes the management of the user's personal information, login password, operation role, and other contents.

(3) BP neural network evaluation and random matrix module: This module includes sample data maintenance, BP neural network and random matrix training, BP neural network and random matrix evaluation, and other sub-modules. Its function is to complete the management, training, and evaluation. Using BP neural network and random matrix analysis tools to train the teaching evaluation data of different personnel, establish a teaching evaluation prediction model. Then, use the dynamic data exchange technology to send the trained network model back to the server, and the system predicts and displays the teaching quality by calling the model.

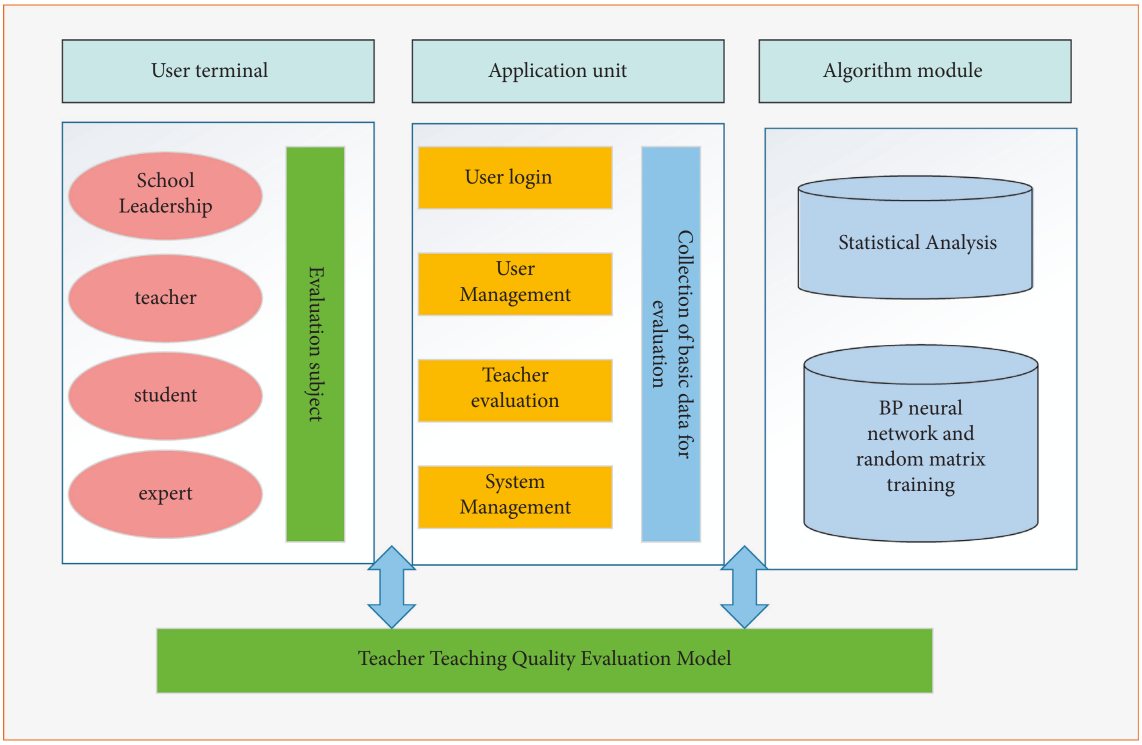

FIGURE 1: Functional structure diagram of system model.

(4) Teacher evaluation: This part contains four parts, namely, student evaluation, institutional evaluation, teacher evaluation, and expert evaluation, which is regarded as the core of the whole system.

(5) Statistical analysis: The main function of this module is to provide operations for users with data query and statistical operation permissions [17]. This part mainly includes data query and result analysis and statistical function under certain conditions. For example, teachers can query their own teaching evaluation results, personal data, and other information, teaching administrators can query the evaluation results of teachers in their own units, and school leaders can compare and analyze the query results and view the final results.

(6) System management function: System management function is entrusted to the system administrator to operate, including basic information management, and user and role maintenance [18].

3.2. Normalization of Evaluation Indicators. The evaluation indexes should reflect the teaching process comprehensively and objectively as much as possible, and reduce the number of evaluation indexes as much as possible. In order to ensure the accuracy of the evaluation results, different index systems should be formulated for different evaluation subjects, that is, students, peer teachers, and supervision experts; different types of courses have different evaluation indicators. The method of qualitative analysis is used to preselect the evaluation index, and the final evaluation index system is established by further analysis through the analytic hierarchy process. "Teaching" and "learning" are the two main subjects in teaching activities, and the evaluation indexes are determined according to the students and teachers who are most familiar with the teaching process and characteristics. The evaluation indicators are shown in Table 1.

As the input features have different numerical ranges, and the numerical ranges of different features vary greatly, the sample data are normalized [19]. The excitation function of the improved BP neural network and random matrix is an s-type function, and the derivative of the function changes within a larger definition domain within the range of [0, 1] or [−1, 1]. The normalized processing of sample data is conducive to the network convergence as soon as possible. Normalize the input data to [0, 1] or [−1, 1]. Commonly used methods have the following three transformation formulas, as shown in the formula.

$$k_m = \frac{p_i\left(p_i + p_{\min}\right)}{\left(p_{\max} + p_{\min}\right)^2},$$
$$p_{mi\,d} = \frac{p_i}{p_{\max}}\left(p_{\max} + p_{\min}\right) \times \frac{1}{2}, \qquad (1)$$
$$k_m = \frac{1}{p_i} \times \left(p_i - p_{mi\,d}\right)\left(p_{\max} + p_{\min}\right)^i.$$

Among them, P_i and K_m represent the re-processing data and the post-processing output data, $P_{\max}$ represents the maximum value in the data, and $P_{\min}$ represents the minimum value in the data.

Table 1: Primary and secondary indicators.

Level 1	Teaching attitude			
Level 2	Instrument (p1)	Standard ($p2$)	Communicate ($p3$)	Job counseling ($p4$)
Level 1	Teaching content			
Level 2	Diverse form ($p5$)	Information ($p6$)	Promoting content ($p7$)	Content update ($p8$)
Level 1	Teaching skills			
Level 2	Reality ($p9$)	Vitality ($p10$)	Innovation ($p11$)	Enthusiasm ($p12$)
Level 1	Teaching effect			
Level 2	Application ($p13$)	Test score ($p14$)	Overall effect ($p15$)	

Table 2: Sample data normalization processing table.

Index	$P1$	$P2$	$P3$	$P4$	$P5$	$P6$	$P7$	$P8$	$P9$	$P10$	$P11$	$P12$	$P13$	$P14$	$P15$
1	0.84	0.92	0.74	0.93	0.84	0.82	0.85	0.92	0.72	0.91	0.82	0.8	0.84	0.92	0.71
2	0.87	0.83	0.71	0.77	0.75	0.87	0.87	0.83	0.71	0.79	0.78	0.87	0.87	0.83	0.71
3	0.85	0.87	0.84	0.93	0.76	0.93	0.85	0.84	0.84	0.93	0.76	0.89	0.85	0.87	0.81
4	0.84	0.76	0.73	0.82	0.91	0.8	0.84	0.76	0.73	0.84	0.93	0.8	0.84	0.76	0.74
5	0.81	0.85	0.82	0.75	0.89	0.83	0.83	0.85	0.83	0.75	0.89	0.83	0.81	0.85	0.82
6	0.89	0.76	0.75	0.94	0.84	0.82	0.89	0.79	0.75	0.94	0.82	0.82	0.89	0.76	0.75
7	0.91	0.85	0.78	0.86	0.87	0.87	0.91	0.85	0.78	0.86	0.87	0.87	0.91	0.85	0.78
8	0.89	0.9	0.65	0.77	0.75	0.84	0.89	0.9	0.65	0.77	0.78	0.84	0.89	0.9	0.68

In order to improve the computational efficiency of the BP neural network and random matrix model, sample data are normalized, as shown in Table 2.

3.3. BP Neural Network and Random Matrix Evaluation Model. The improved BP neural network and random matrix have strong nonlinear mapping ability, which can discover the linear and nonlinear laws between data from complex and large number of data patterns. The traditional BP neural network is composed of input layer, hidden layer, and output layer [20], while the improved BP neural network and random matrix model are composed of input layer, hidden layer, random application layer, and output layer. In the case that there are enough samples to train, the network is allowed to correct the appropriate weights, and then the evaluation results of teaching quality are predicted according to the sample data. The process of BP neural network and random matrix model established in this paper is shown in Figure 2.

3.3.1. Design of Input Layer. There are 15 secondary indicators, $m = 15$.

3.3.2. Design of Output Layer. In this paper, the evaluation results are taken as the output of BP network and random matrix. Therefore, $n = 1$.

3.3.3. The Design of Hidden Layers. According to the structural characteristics and training process of the improved BP neural network and random matrix, the more the hidden layers, the more difficult the BP network model. According to Cosmogony theory, we choose BP network and random matrix with only one hidden layer structure. The structure of BP network and random matrix with four layers is simple and easy to realize.

3.3.4. Determination of the Number of Hidden Layer Neurons

$$L = \sum_{S}^{t} (s + t) - \frac{\pi}{s}, \qquad (2)$$

where L is the number of neurons in the hidden layer, S is the number of neurons in the input layer, and t is the number of neurons in the output layer. According to the formula, the number of hidden layer neurons should be selected between 6 and 20. After many experiments and adjustments, the BP neural network and random matrix structure in this paper have the best performance when L is 15.

3.3.5. Determination of Neuron Activation Function. The main function of the sigmoid activation function is to complete the nonlinear transformation of the data and solve the problem of insufficient expression and classification ability of the linear model. Considering the needs of this paper and the advantages of sigmoid function in classification and function approximation, the equation is as follows:

$$f(z) = \frac{1}{z} \left(2 + g^{z}\right)\left(2 - g^{z}\right). \qquad (3)$$

Among them, g represents the hidden layer input, and $f(z)$ represents the hidden layer output.

3.3.6. Random Application Layer. The random matrix represents the random matrix applied to the probability distribution, which redistributes the probability mass of the

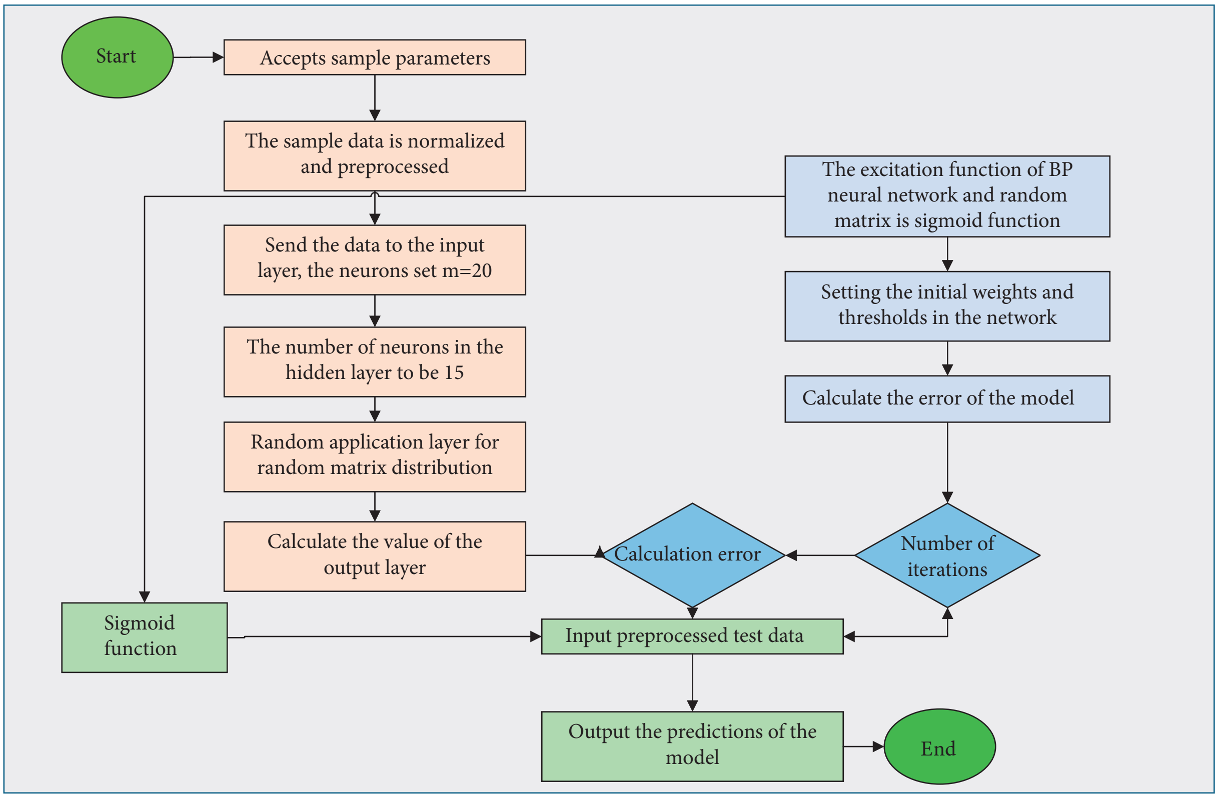

Figure 2: Model flowchart.

original distribution while maintaining its total mass [21]. When this process is applied repeatedly in the random application layer, the distribution of evaluation results converges to a stationary distribution.

The probability of moving from a to b in a time step is

$$Rw(a\|b) = R_{a,b}. \tag{4}$$

The elements of row a and column b of the random matrix R are given:

$$R = \begin{Bmatrix} R_{1,1} & R_{1,2} & \cdots & R_{1,a} & \cdots \\ R_{2,1} & R_{2,2} & \cdots & R_{2,a} & \cdots \\ \vdots & \vdots & \ddots & \ddots & \ddots \\ R_{a,1} & R_{a,2} & \cdots & R_{a,b} & \ddots \end{Bmatrix}. \tag{5}$$

Since the sum of the probabilities from state a to the next state must be 1, this matrix is a right random matrix; then,

$$\oint R_{a,b} = \sum_{b}^{a} R = 1. \tag{6}$$

3.3.7. Determination of Model Structure. According to the parameters determined in the above steps, the BP neural network and random matrix model structure can be determined as the 15–15–1–1 four-layer BP neural network and random matrix structure, as shown in Figure 3.

3.3.8. Parameter Initial Design. When using BP neural network and random matrix for training modeling, it is necessary to set a range of initial weights and thresholds in the network in advance, in order to ensure that the training does not fall on those flat regions and fall into local minimum values at the beginning. When setting weights, small random numbers are generally used.

3.4. Evaluation of Teaching Effect Index. The evaluation of students' examination results is an important index. Evaluating teaching quality based solely on grades without considering the basic differences of students, the conclusions drawn may not reflect the actual situation. Therefore, the results are unconvincing. In order to reflect the fairness of evaluation, BP neural network and random matrix model are used to evaluate students' examination results.

Progress ($m > n$) is that which cultivates m students into n students. In general, the cultivation of m students into n students is a regressive phenomenon ($m < n$). The formula is as follows:

$$V_{mn} = \sqrt{(m-n)^4} \times T_{mn} \times (m-n)^4 x_{mn}, \tag{7}$$

where m, $n = 1, 2, \ldots, m$ is the transfer progress of T_{mn}, where $(m-n)^4$ is the weight of T_{mn}.

$$V = (V_{mn}) * (m-n)^4 x_{mn} \times \frac{x_{mn}}{y_m}, \tag{8}$$

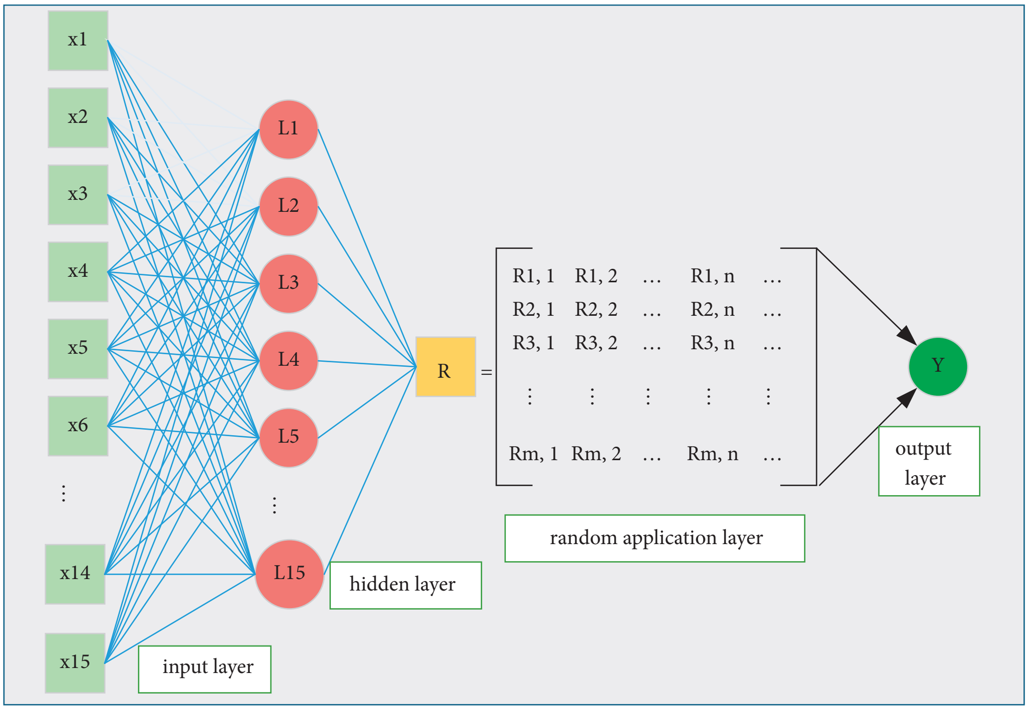

Figure 3: BP neural network and random matrix model structure.

Table 3: Experimental environment construction.

Lab environment	Python 3.7
Learning framework	TensorFlow 2, the second-generation artificial intelligence learning system based on data flow graph developed by Google
Learning library	A deep learning library based on TensorFlow and Theano written in pure Python

where $(m-n)4$ represents the weight of progress or regression. As long as you progress, the weight is positive, and when you regress, the weight is negative.

It is called the improved BP neural network and the progressive matrix of random matrix T.

$$E(V) = \sum_{mn}^{x} \frac{x_{mn}}{y_{mm}} = \sum_{m,n=1}^{x} (m-n)^4 \left(\frac{x_{mn}}{y_m}\right). \tag{9}$$

It is called the efficiency degree. With the efficiency degree, the teaching efficiency can be compared according to the value of $E(V)$.

4. Experiment Design

4.1. Experimental Environment Construction. The experimental environment of this paper is based on Python 3.7, which can well support Python and C++ program development language, and is the most popular artificial intelligence learning framework at present. On top of this is the deep learning library based on TensorFlow and Theano, which is written in pure Python. It is also the API of TensorFlow and Theano high-level neural network. Keras library can save developers too much attention to the low-level details and enable developers to bring ideas to life quickly. The experimental environment construction is shown in Table 3.

4.2. The Evaluation Index. The experiment divided the curriculum evaluation data from 2015 to 2020 into 1372 samples as the training data set and 191 samples from 2021 as the test data set. Through the input test data for verification, the evaluation and prediction results are reversely normalized. Compared with the traditional evolutionary algorithm (GA, BSA), the mean square error, prediction accuracy, training time, and iteration times were used to evaluate. The meaning of the evaluation indicators is shown in Table 4.

5. Results and Analysis

5.1. Model Parameter Analysis. It is more effective to introduce single S-type function as training function of BP neural network and random matrix than traditional evolutionary algorithm. In this experiment, the training time, iteration times, mean square error, and prediction accuracy index are compared to obtain the average value of the proposed algorithm and the traditional evolutionary algorithm. The MSE and prediction accuracy comparison of the two algorithm models is shown in Table 5.

The results show that when the single S-type function is introduced, the prediction accuracy of the proposed algorithm reaches 94.9% when the number of iterations is 133, which is 2.41% higher than the traditional evolutionary

Table 4: The meaning of evaluation indicators.

Square error	Root mean squared error is the arithmetic square root of the mean squared error.
Prediction accuracy	Accuracy refers to the degree to which a thing is predicted or described correctly
Training time	Training time is the time spent training
Iteration times	The number of iterations is the number of times the process is repeated

Table 5: MSE and prediction accuracy comparison model.

Algorithm	Gradient decline	BP neural network and random matrix model
MSE	56.4125	22.63
Accuracy	92.49%	94.90%
Training time	11.511	0.603
Iterative number	5000	133

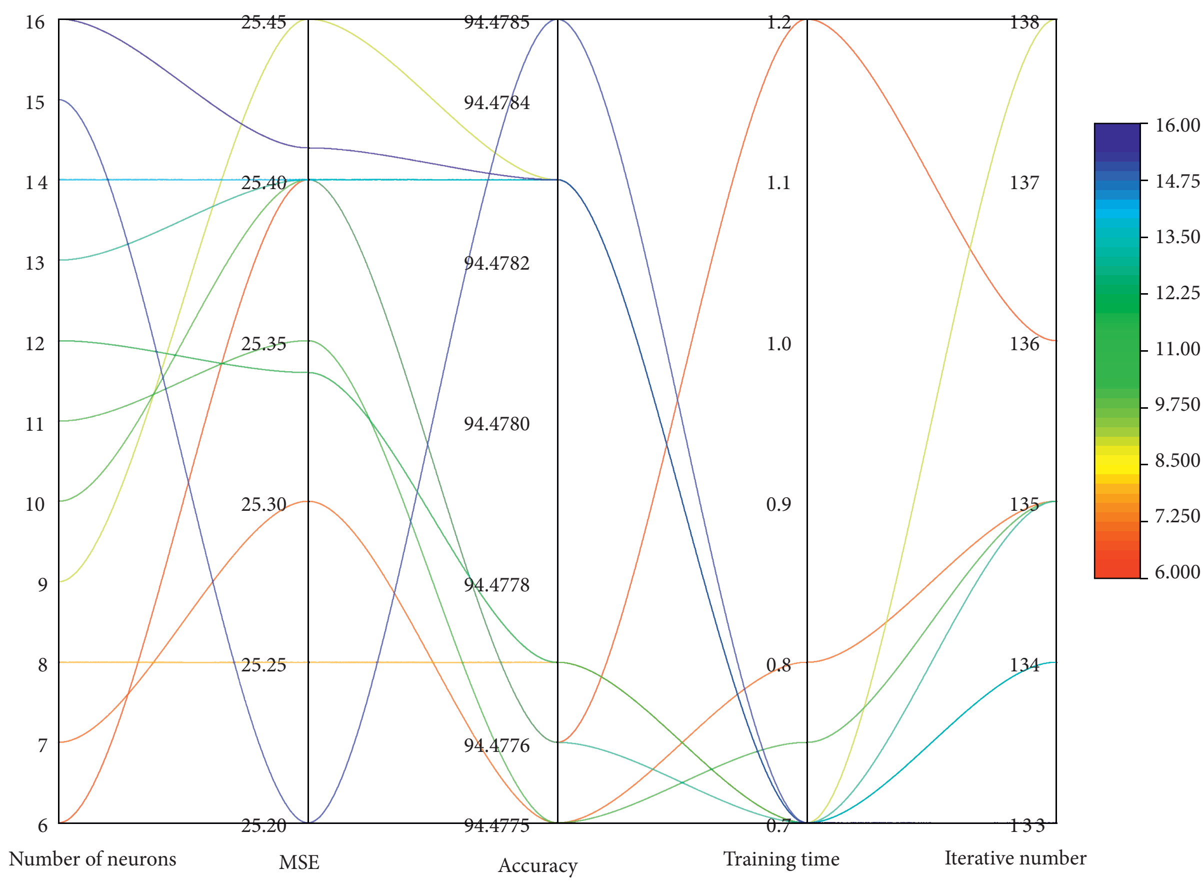

Figure 4: Change curves of iteration times, training time, MSE, and prediction accuracy.

algorithm. The shortest training time is 0.603 s, while the traditional evolutionary algorithm is 12.311 s. The mean square error is 24.33, while the traditional evolutionary algorithm is 56.3619. It further shows that BP neural network and random matrix algorithm are more effective than traditional evolutionary algorithm.

It is known that the characteristic dimension of the input data is 20 and the target label of the output is 1. Training single S-type function input model to obtain stable model verifies the test data set input. As the number of neurons changes, the evaluation index also changes greatly, as shown in Figure 4.

It can be seen from Figure 4 that when the number is 15, the mean square error of the model is the smallest and the error is 25.1. The prediction accuracy was 94.78%. The training time of the model is very ordinary, and the number of iterations is not different. In general, when the parameter is set to 15, the overall performance index of the model is the best.

In order to ensure the convergence speed of the model in the training process, when the number of neurons is 15, the momentum term of the training function is set as 0.85, and the curves of the mean square error and prediction accuracy are obtained, as shown in Figure 5.

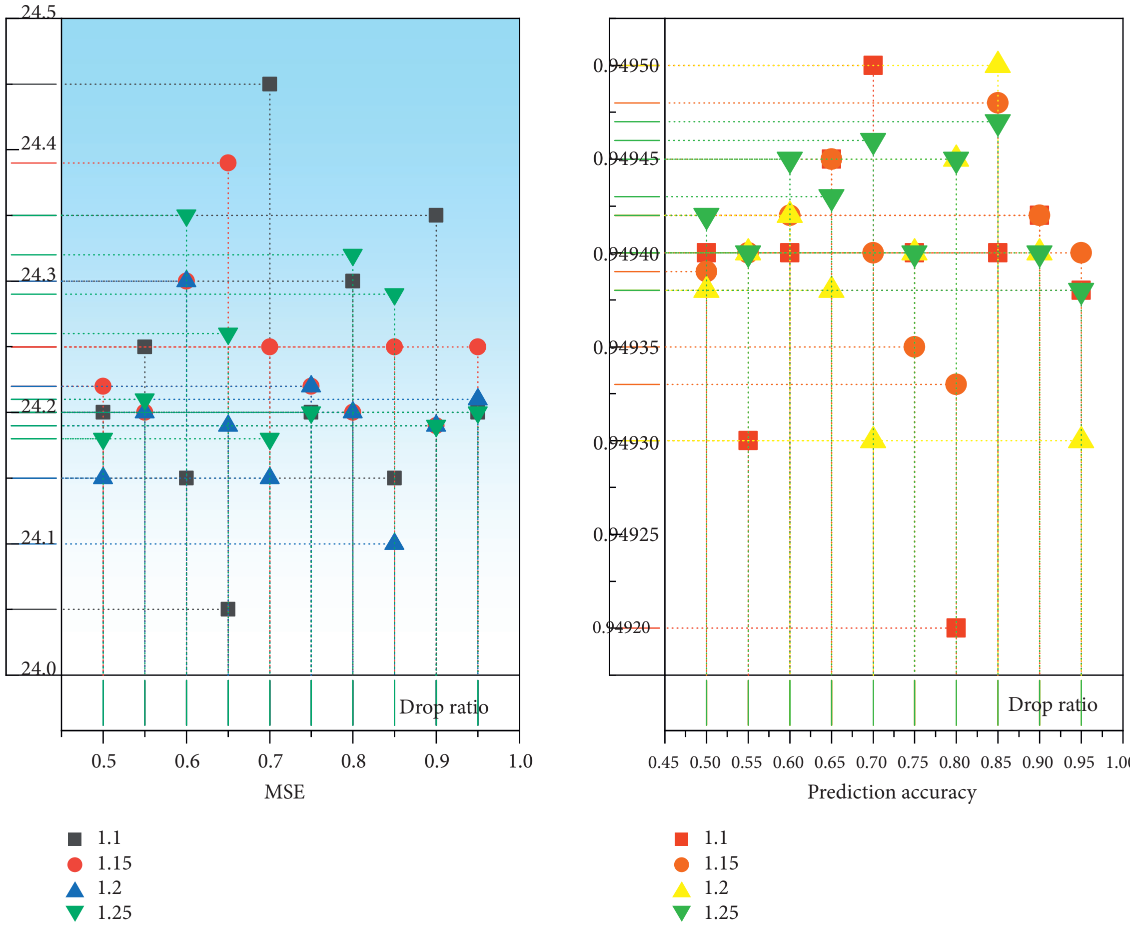

Figure 5: MSE and prediction accuracy curve.

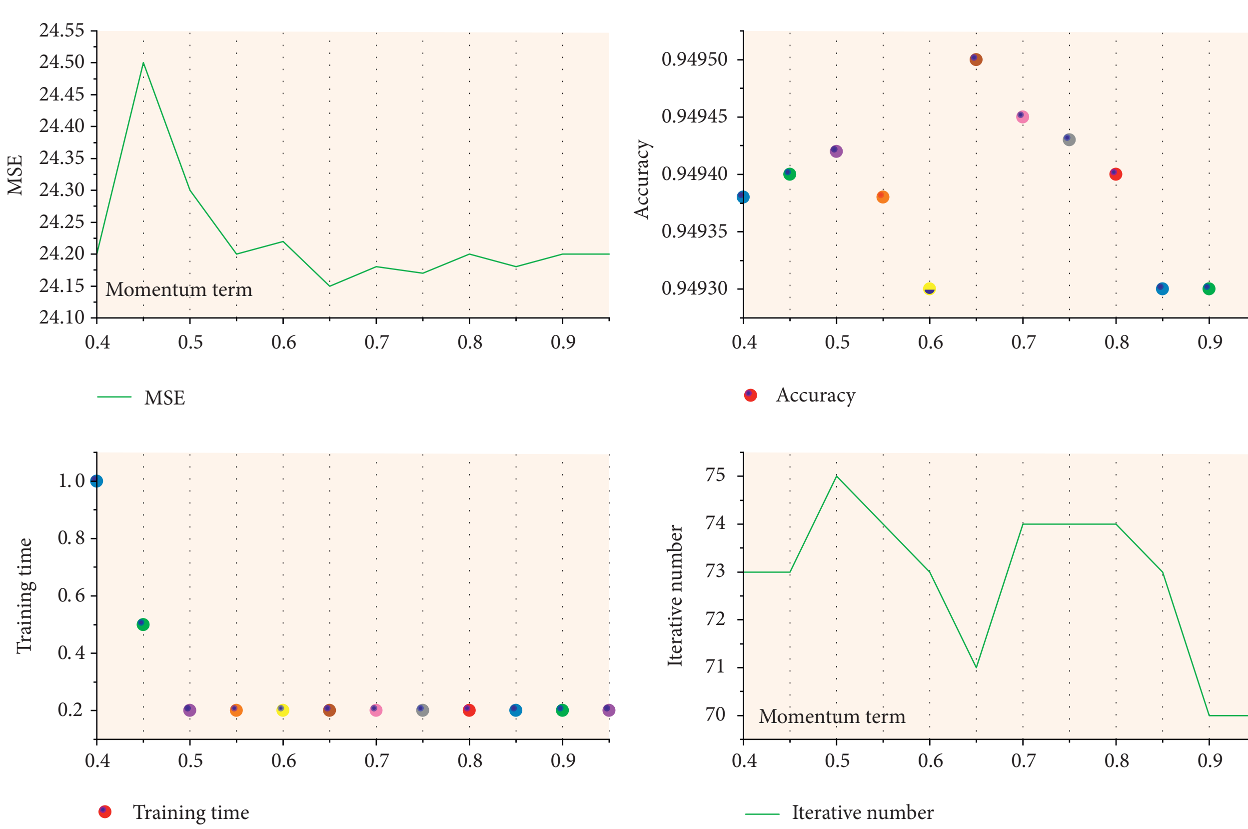

Figure 6: Evaluation index change curve.

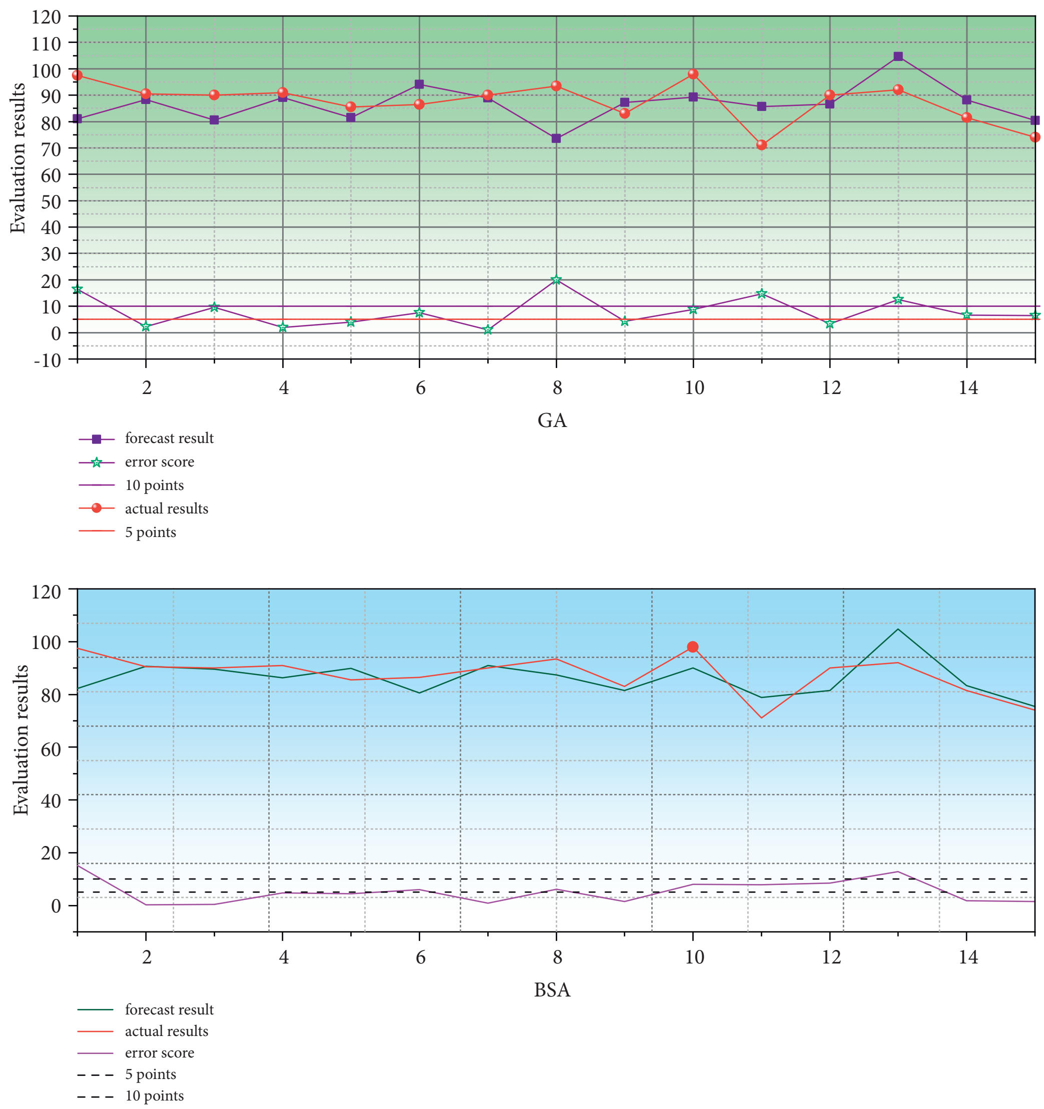

Figure 7: Comparison diagram of different models.

As can be seen from Figure 5, when the growth ratio of learning rate is the same, the mean square error and prediction accuracy are constantly fluctuated with the increase of its decline ratio. When the decrease ratio of learning rate is the same, the mean square error and prediction accuracy increase first and then decrease. According to the data analysis and comparison in the figure, when the adaptive ratio of learning rate is 1.2 and the decline ratio is 0.85, the error of the model is the smallest and the accuracy is the highest.

The training function of the given model is single S-type function, the number of hidden layer neurons is 15, and the combination of the increase ratio and decline ratio of adaptive learning rate is 1.2 and 0.85. The change curve of model evaluation indexes is shown in Figure 6.

When the convergence accuracy is lowest, the momentum term is 0.65. When the prediction accuracy is highest, the momentum term is 0.65. Therefore, the performance of the model is the best when the momentum term is 0.65.

5.2. The Improved Model Is Compared and Analyzed. In order to verify the effectiveness of BP neural network and stochastic matrix model, the improved model was compared with GA and BSA traditional evolution models, and each model was run for 15 times to get the average value. The model comparison is shown in Figure 7.

Although traditional evolutionary algorithms (GA and BSA) can generate prediction results according to students' scores, it can be seen from the 15 groups of evaluation data in the figure that the evaluation results of GA and BSA are relatively floating, and some evaluation results even exceed the normal scoring range (100 points). However, BP neural network and random matrix algorithm can predict students' scores in the range of scores, whether improved or not.

Figure 8 compares the evaluation results in the last 15 groups of test sample data of the BP neural network evaluation model with BP, GA, and BSA.

As can be seen from the data in Figure 8, GA and BSA, the evaluation results of the improved BP neural network and the random matrix evaluation model of test error are bigger, and

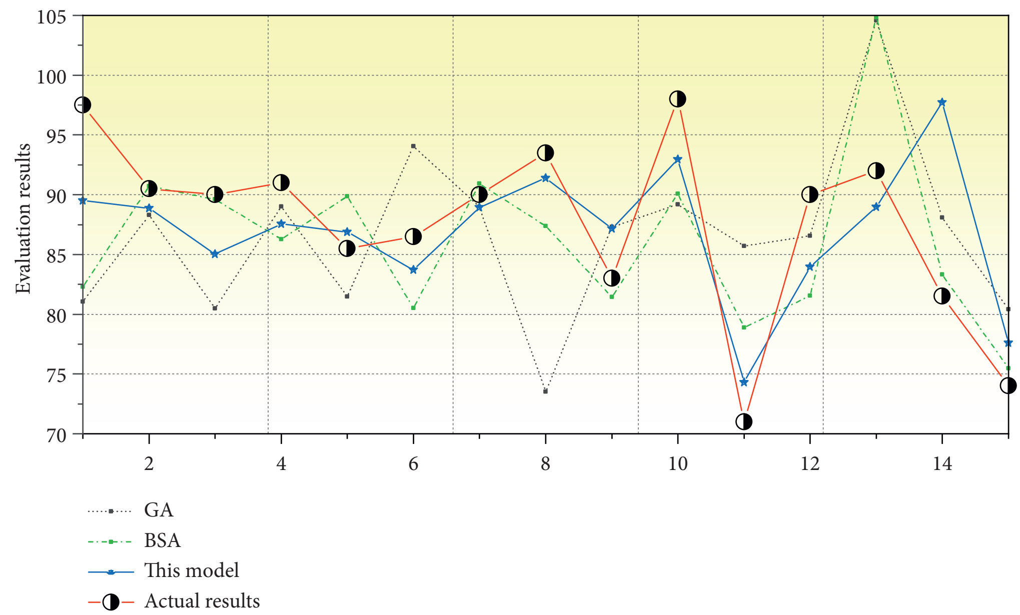

FIGURE 8: The evaluation results of this model are compared with GA and BSA.

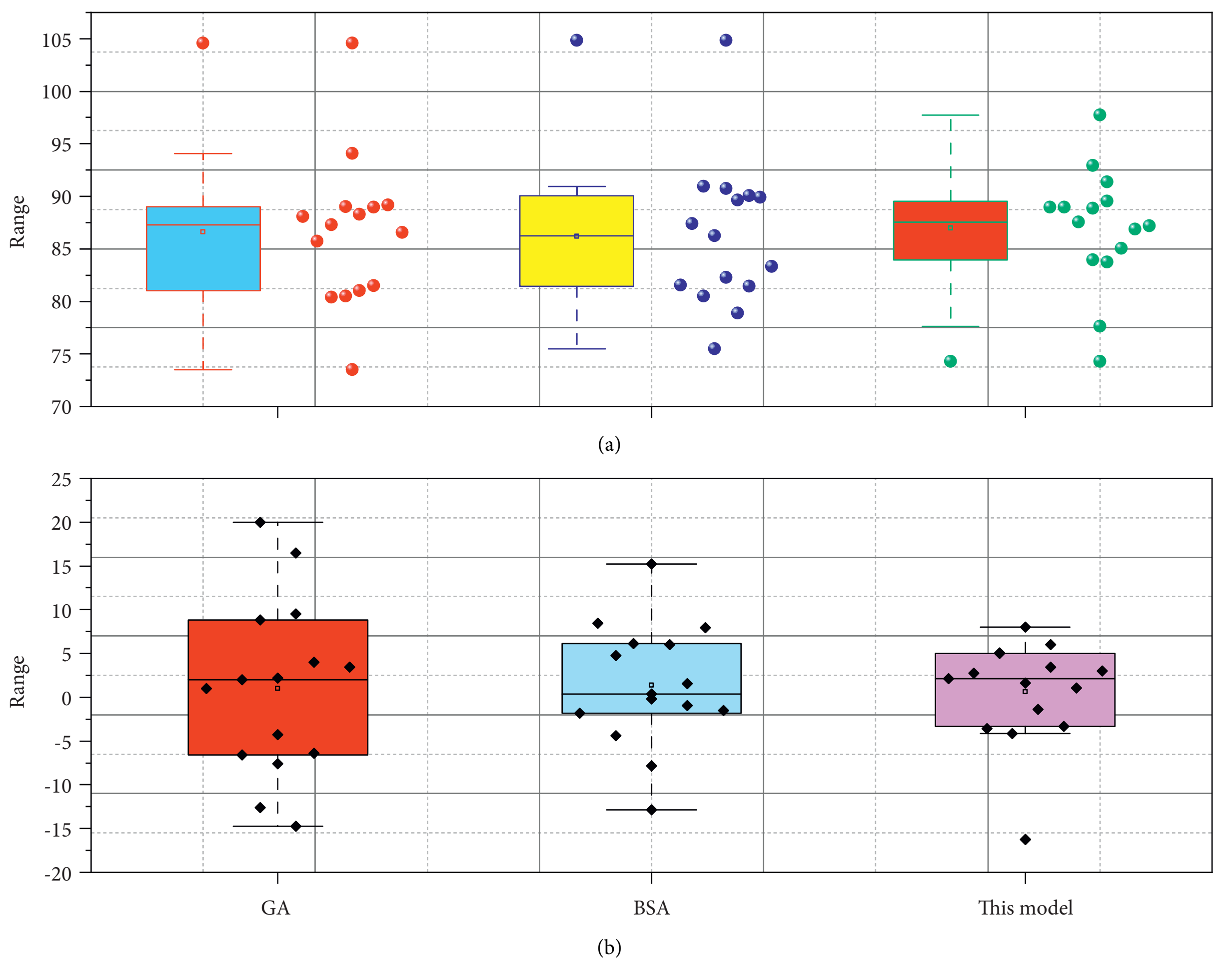

FIGURE 9: Evaluation results and error comparison box diagram. (a) Evaluation results. (b) Evaluation error.

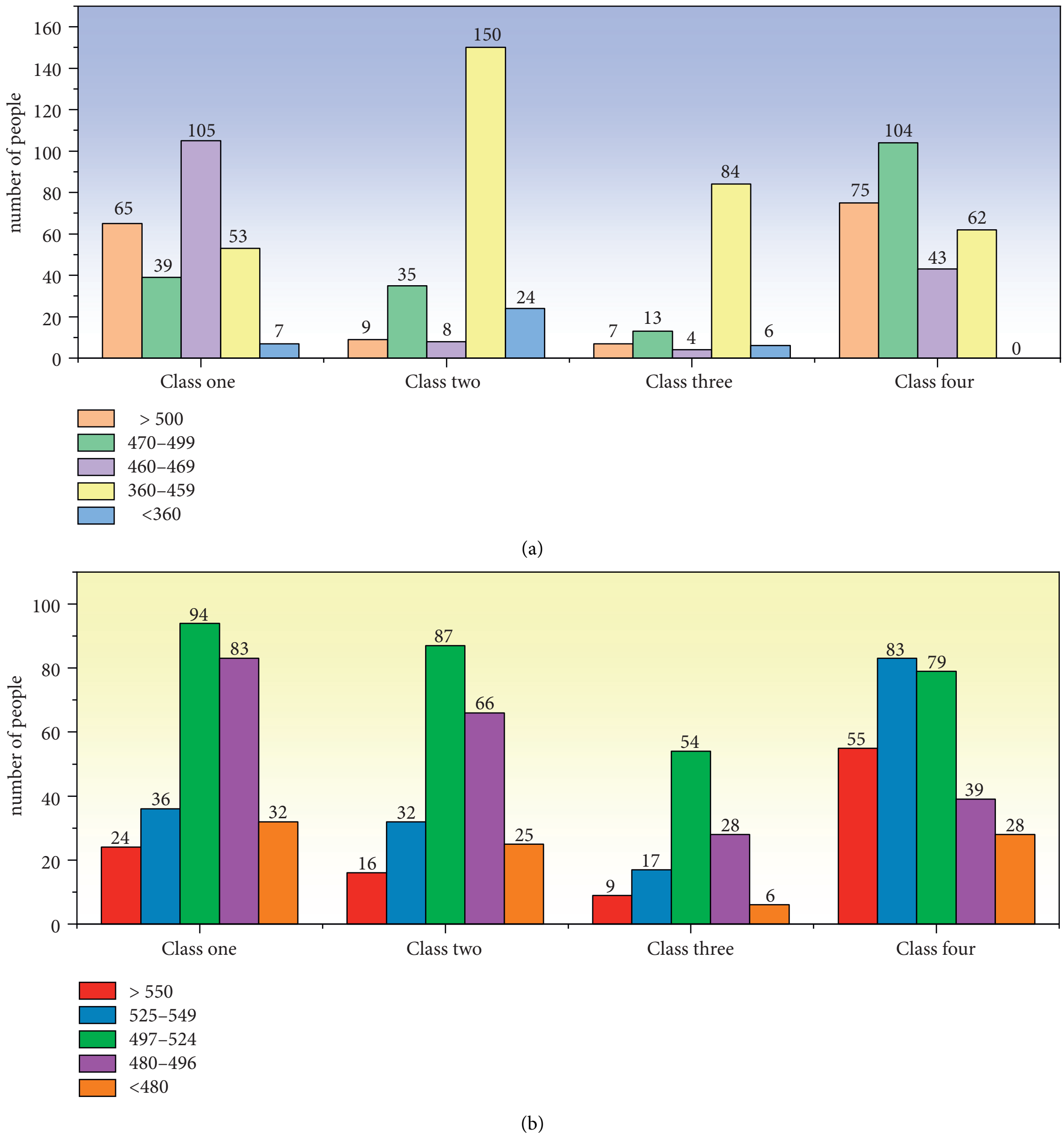

Figure 10: Grade distribution map of four classes. (a) Entrance exam. (b) Final exam.

the improved evaluation model predicted results consistent with the actual result, and compared with other three minimum error, this results in the evaluation results and error to make compare the box figure of the more obvious. See Figure 9.

Although the evaluation results of GA and BSA algorithms are a little smaller than those of BP neural network, extreme data appear in both algorithms. However, the error of the model evaluation results is controlled in a good range, and the maximum error is less than 8 points. Therefore, it can be concluded that the improved model is better in the evaluation accuracy.

5.3. The Model Analyzes the Teaching Evaluation Index. Taking A university as an example, this project selects 922 students from Class 1, Class 2, Class 3, and Class 4 of 2020 as investigation samples. The random matrix algorithm is used to evaluate teachers' teaching performance on the two scores of entrance examination and final exam. The distribution of the results of the four classes is shown in Figure 10.

As can be seen from Figure 10, the performance of Class 4 was better than that of Classes 1, 2, and 3 in the whole school year, mainly in the range of over 497 points. There were 217 students in Class 4, 154 students in Class 1, 135 students in Class 2, and 80 students in Class 3. By comparing the admission scores, it can be seen from definition 3 that $E(V1) = 4.103$, $E(V2) = -8.779$, $E(V3) = 7.642$, and $E(V4) = 1.086$. Class 3 is the most efficient, class 1 is the second, Class 4 is the third, and Class 2 is the fourth. Therefore, in the evaluation of teachers' teaching effect indicators, the teaching effect of class 3 teachers is the best.

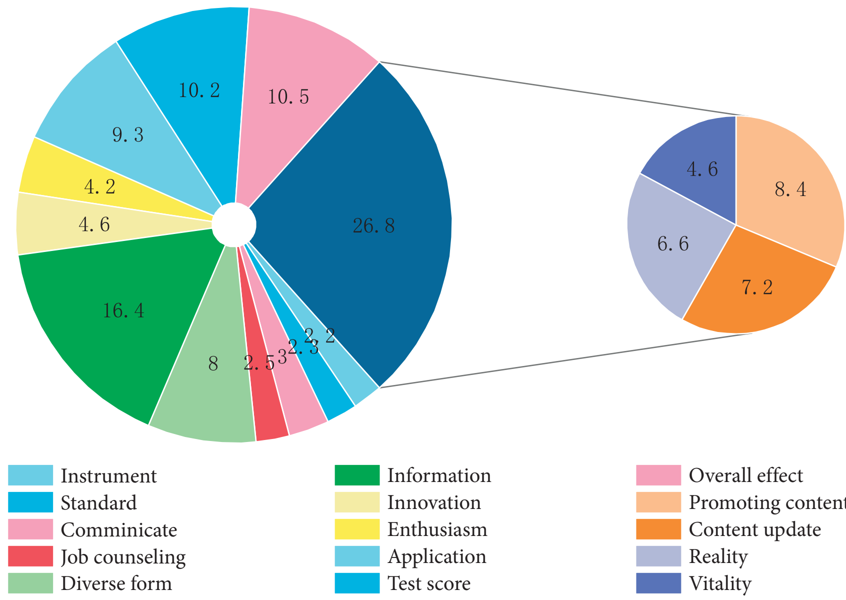

Figure 11: Index weight chart.

Finally, combining BP neural network algorithm and random matrix algorithm, the final evaluation index of undergraduate university A is shown in Figure 11.

It can be seen from the weight of first-level indicators, teaching content > teaching effect > teaching skills > teaching attitude. In teaching content, the weight of the information is the highest. In the index of teaching skills, the combination of theory and practice is higher than innovation and enthusiasm. Finally, the conclusion is drawn that the comprehensive index design is simple and suitable for the school situation, and can highlight the fairness, scientific, and measurable evaluation.

6. Conclusion

This paper mainly focuses on the design of the teaching quality evaluation model of higher education teachers based on BP neural network and random matrix, and conducts in-depth research on the normalization of the evaluation indicators, the construction of BP neural network and random matrix evaluation model, and the evaluation of teaching effect indicators. Through the research, it is found that the model in this paper can improve the accuracy and availability of evaluation prediction, and finally verify the fairness and scientifically of teacher teaching quality evaluation index system. In the future work, it is necessary to verify and improve the evaluation index system in a wider sample space, a longer time range, and a more professional academic level. Efforts will be made to make this system a general platform that can be widely used in the quality evaluation of various colleges and universities.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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