Teaching Quality Evaluation of Animal Science Specialty Based on IPSO-BP Neural Network Model

Liyan Chen, Lihua Wang, and Chunyou Zhang

College of Animal Science and Technology, Inner Mongolia Minzu University, Tongliao 028000, China

Correspondence should be addressed to Lihua Wang; wanglihua7967@imun.edu.cn

Received 29 May 2022; Revised 24 June 2022; Accepted 1 July 2022; Published 23 September 2022

Academic Editor: Gengxin Sun

Copyright © 2022 Liyan Chen et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Teaching quality evaluation is one of the most commonly used educational evaluation methods, which is used to evaluate teachers' teaching ability and teaching effect. In order to improve the effectiveness and accuracy of teaching quality evaluation, a BP neural network model based on improved particle swarm optimization (IPSO) is proposed. Firstly, the evaluation index system of teaching quality is constructed with teaching attitude, teaching content, teaching method, and teaching effect as indicators. Then, IPSO algorithm is used to optimize the weight and threshold of neural network to improve the performance of BP algorithm. Secondly, IPSO-BP algorithm is used for sample training to optimize the model structure. Finally, the model is used to evaluate the teaching quality of animal science-related courses in Inner Mongolia University for Nationalities. The results show that compared with the ordinary BP neural network model, the IPSO-BP model has fast convergence speed, good robustness, and strong global search ability, and the evaluation accuracy rate is 96.7%. It is feasible in the evaluation of teaching quality.

1. Introduction

Teaching quality is not only the lifeline of the survival and development of higher education but also an important link to measure the teaching management and teaching effectiveness of colleges and universities. Through the quantitative evaluation of teachers' teaching activities by different subjects, we can judge the teaching effect, test whether the expected teaching objectives have been achieved, and test the students' ability to accept the teaching process [1]. Teaching quality evaluation is a fuzzy nonlinear problem, which has the characteristics of wide evaluation content and many evaluation indexes. Therefore, there are often some problems in the evaluation process, such as imperfect evaluation index system, unscientific evaluation methods, and so on. Therefore, how to improve the scientificity and effectiveness of teaching quality evaluation is the focus of researchers.

Foreign scholars have studied the evaluation of teaching quality earlier. Among them, the teaching effect evaluation index system proposed by scholars Zhou is the most representative [2]. Later, scholars made continuous improvement on the evaluation methods. Fuzzy comprehensive evaluation method [3], grey system theory [4], analytic hierarchy process, and support vector machine are widely used to further improve the reliability of evaluation. Although these methods consider the corresponding relationship between teaching quality and evaluation indexes [5, 6], it is difficult to eliminate the problems of subjectivity and randomness in the process of evaluation, and they have some limitations on the nonlinear evaluation of teaching quality. Therefore, it is necessary to establish a scientific teaching quality evaluation index system according to the characteristics of different courses and students, measure the factors affecting teaching quality from multiple levels, angles, and directions, and establish an evaluation model based on intelligent control algorithm, so as to improve the accuracy of teaching quality and provide a scientific basis for teaching management and decision making.

BP neural network can simulate the nervous system of human brain, can accurately approximate any nonlinear function, has strong data analysis ability and self-learning ability, and is widely used in various fields [7]. In recent years, many scholars have been trying to apply it to the process of teaching quality evaluation, which has greatly
improved the accuracy of teaching quality evaluation. However, because the descent learning method adopted by BP neural network is a local search method, the convergence speed is slow, which makes the neural network easy to fall into local minimum and have weak generalization ability.

Based on the existing research, this paper constructs an IPSO-BP neural network model, which uses particle swarm optimization algorithm to optimize the weight and threshold of neural network, so as to improve the performance of BP algorithm, shorten the training time of neural network, and improve the search efficiency and accuracy. At the same time, the trained IPSO-BP neural network model is used to evaluate the teaching quality of colleges and universities, verify the reliability and feasibility of the model, and provide a theoretical basis for examining teachers’ teaching effect, improving teaching methods, and optimizing teaching management process.

2. Construction of Teaching Quality Evaluation Index System

2.1. The Role of Teaching Evaluation

2.1.1. Teaching Effect Test. Teaching evaluation itself is also a kind of teaching activity, which can quantitatively evaluate teachers’ teaching activities through different subjects, so as to determine the teaching effect, test whether teachers can complete the corresponding teaching tasks and achieve the expected teaching objectives, and test students’ acceptance of the teaching process.

2.1.2. Teaching Feedback and Guidance. Through the feedback of teaching evaluation information, teachers can understand their own teaching effect and students’ learning situation, timely optimize the teaching mode, and modify the teaching means, so as to continuously improve the teaching quality and the effectiveness of classroom learning.

2.1.3. Regulating Teaching Management. Teaching evaluation can be used to verify whether the school teaching management is standardized, institutionalized, and scientific, monitor teachers’ teaching quality, and master students’ learning dynamics, so as to adjust teaching plans and educational objectives and to improve the teaching quality evaluation system.

2.2. Teaching Quality Evaluation Index System. Because there are some individual differences between teaching participants and evaluators, it is difficult to draw scientific and effective conclusions by direct teaching evaluation. Therefore, it is necessary to establish a teaching quality evaluation system, find out the index factors that can directly reflect the teaching effect, and then establish an evaluation model based on the index factors, so as to carry out comprehensive evaluation [8].

Scientific and effective evaluation results depend on a reasonable and standardized index system. This paper establishes the evaluation index system of teaching quality through in-depth investigation. It includes four primary indicators: teaching attitude, teaching content, teaching method, and teaching effect, which are expressed by \(A_1, A_2, A_3,\) and \(A_4\) respectively. It is subdivided into 16 secondary indicators, represented by \(A_{11}, A_{12}, A_{13},..., A_{43},\) and \(A_{44}\) respectively. At the same time, the index weight is allocated according to the expert experience and the actual teaching situation of the unit, as shown in Table 1.

3. BP Neural Network Model

3.1. Structure and Principle of BP Neural Network. Backpropagation (BP) is a multilayer feedforward network trained according to the error backpropagation algorithm. It can simulate the human brain nervous system and learn and modify the input information, so as to achieve objective and fair information output. Its model structure mainly includes input layer, hidden layer, and output layer. BP neural network continuously optimizes the network by modifying the thresholds between the input layer, hidden layer and output layer, so as to minimize the error between the output value and the target value. It is widely used in machine learning, artificial intelligence, information prediction and other fields [9].

BP neural network can approach any nonlinear function infinitely. Its learning process is divided into two stages: signal forward propagation and error backpropagation. When the signal propagates forward, the input sample is transmitted from the input layer, processed by the hidden layer, and then transmitted to the output layer. Compare the actual output results with the target output results. If they are inconsistent, it will turn to the backpropagation stage of error. Backpropagation is to transfer the output error back to the input layer in some form through the hidden layer, distribute the error to each neuron, and constantly correct the connection weight and threshold between each layer, so that the error decreases along the gradient direction until the output error reaches the preset accuracy or reaches the set maximum learning times [10]. BP neural network usually adopts three-layer network structure, as shown in Figure 1.

Let the input data and output data of training samples be \(x(t)\) and \(y(t)\), respectively, the input vector of BP neural network be \(X = (x_1, x_2, ..., x_i)^T\), and \(i\) be the number of nodes in the input layer. The output vector of the output layer is \(Y = (y_1, y_2, ..., y_k)^T\), and \(k\) is the number of nodes of the output layer.

The output expression of the hidden layer is

\[
H_j = \sum_{i=1}^{m} \omega_{ij}x_i - \theta_j \tag{1}
\]

Select the sigmoid function to build the mapping relationship, and the function expression is

\[
f(x) = \frac{1}{1 + e^{-x}} \tag{2}
\]

where \(\omega_{ij}\) is the weight between the input layer and the hidden layer; \(\theta_j\) is the threshold of the hidden layer; and \(m\) is the number of nodes in the hidden layer.
The output expression of the output layer is

\[ L_k = \sum_{j=1}^{k} \omega_{jk} b_j - \theta_k, \]  \hspace{1cm} (3)

where \( \omega_{jk} \) is the weight between the hidden layer and the output layer and \( \theta_k \) is the threshold of the output layer.

Define the error between the actual output and the target output as

\[ E = \sum_{k=1}^{m} (L_k - Z_k)^2, \]  \hspace{1cm} (4)

where \( L_k \) is the actual output and \( Z_k \) is the target output.

The learning and training process of BP neural network is the process of continuously adjusting the weight and threshold according to the error \( E \), so that the actual output of training gradually converges to the expected output until the iteration reaches the set upper limit or the prediction accuracy reaches the threshold.

The gradient descent method is applied to update the weight, and the expression is [11]

\[
\begin{align*}
\omega_{jk}^{t+1} &= \omega_{jk}^{t} + \eta H_j (L_k - Z_k) \\
\omega_{ij}^{t+1} &= \omega_{ij}^{t} + \eta H_j (1 - H_j) x(i) \sum_{k=1}^{m} \omega_{jk} \left( L_k - Z_k \right).
\end{align*}
\]  \hspace{1cm} (5)

Update the threshold, which is expressed as

Table 1: Teaching quality evaluation index system.

| Primary index          | Weight | Secondary index                      | Weight |
|------------------------|--------|--------------------------------------|--------|
| Teaching attitude (A1) | 0.21   | Mental outlook (A11)                 | 0.18   |
|                        |        | Preparation before class (A12)      | 0.34   |
|                        |        | Attendance rate (A13)               | 0.27   |
|                        |        | Professionalism (A14)               | 0.21   |
| Teaching contents (A2) | 0.23   | Teaching objectives (A21)            | 0.21   |
|                        |        | Teaching ideas (A22)                | 0.32   |
|                        |        | Key points and difficulties (A23)    | 0.22   |
|                        |        | Logic and clarity (A24)             | 0.25   |
| Teaching method (A3)   | 0.27   | Diversification of teaching methods (A31) | 0.26   |
|                        |        | Cultivation of innovation ability (A32) | 0.28   |
|                        |        | Students as the main body (A33)     | 0.24   |
|                        |        | Combining theory with practice (A34) | 0.22   |
| Teaching effectiveness (A4) | 0.29 | Classroom atmosphere (A41)      | 0.21   |
|                        |        | Teacher student interaction (A42)   | 0.19   |
|                        |        | Knowledge mastery (A43)             | 0.32   |
|                        |        | Problem solving ability (A44)       | 0.28   |

Figure 1: Basic structure of BP neural network.
4 Computational Intelligence and Neuroscience

search ability. Moreover, the addressing process no longer
convergence speed, good robustness, and strong global
formance of BP algorithm. TX_he optimized algorithm has fast
threshold of neural network, and the swarm intelligence
network, PSO algorithm is used to optimize the weight and
optimization tool, PSO is an optimization algorithm based
As an
4.2. Training Process of IPSO-BP Neural Network.

3.2. Process of BP Neural Network
(1) Parameter initialization: set the network structure of
the neural network and the number of nodes in each
layer, assign random values to the weight matrix and
threshold matrix, and assign initial values to pa-
ters such as accuracy and learning rate.
(2) Determine the input vector and the target output
vector.
(3) Calculate the actual output of the hidden layer and
the actual output of the output layer.
(4) The error signal propagates back along the original
direction and modifies the weight and threshold of
each layer. Then, it propagates forward from the
input layer. The two processes are repeated. If the
preset accuracy is reached or the maximum number
of learning times is reached, the learning ends. TX_he
continue with step (5).
(5) The weights and thresholds of the hidden layer and
the output layer are calculated, respectively.
(6) The error signal propagates back along the original
structure at present, but there are still some problems in the
training process:
(1) Slow convergence speed: BP algorithm back-
propagates the error signal through the network and
constantly modifies the weights and thresholds of
neurons at each layer until the desired goal is
achieved. In other words, the error reduction is at the
cost of time.

BP network is the most widely used neural network
structure at present, but there are still some problems in the
training process:
(1) Slow convergence speed: BP algorithm back-
propagates the error signal through the network and
constantly modifies the weights and thresholds of
neurons at each layer until the desired goal is
achieved. In other words, the error reduction is at the
cost of time.

4.2. Training Process of IPSO-BP Neural Network. As an
optimization tool, PSO is an optimization algorithm based
on swarm intelligence theory. Combining PSO with neural
network, PSO algorithm is used to optimize the weight and
threshold of neural network, and the swarm intelligence
generated by particle cooperation and competition is used to
guide the optimization search, so as to improve the per-
formance of BP algorithm. The optimized algorithm has fast
convergence speed, good robustness, and strong global
search ability. Moreover, the addressing process no longer

(2) BP algorithm adopts the gradient descent method to
adjust the network weight and threshold, so it is easy
to fall into the problem of “local minimum.”

4. IPSO-BP Neural Network Model

4.1. Improved Particle Swarm Optimization (IPSO).
Particle swarm optimization (PSO) is an optimization al-
algorithm based on bird predation. In the optimization cal-
culation, the particle velocity and position are updated by
continuously tracking the optimal solution, so as to con-
tinuously seek the optimal solution. It is widely used in the
solution process of optimization problems [12].
If the particle is regarded as a solution vector in an N-
dimensional space, assuming that $x$ and $v$ represent the
spatial position and velocity of particle $i$, respectively,
the particle update strategy can be expressed as [13]
\[
v_{i,d}(t + 1) = \omega v_{i,d}(t) + c_1 r_1 [p_{i,d}(t) - x_{i,d}(t)] + c_2 r_2 [p_{g,d}(t) - x_{i,d}(t)],
\]
\[
x_{i,d}(t + 1) = x_{i,d}(t) + v_{i,d}(t),
\]
where $p_{i,d}(t), p_{g,d}(t)$ are individual optimal solution and
global optimal solution at time $t$; $d$ is the dimension of the
current particle, $d = 1, 2 \ldots N$; $\omega$ is the inertia weight of the
particles; $c_1, c_2$ represent the learning factor; and $r_1, r_2$ are
random numbers evenly distributed between $[0, 1]$.

The traditional particle swarm optimization algorithm is
easy to fall into local optimization and exhibits “premature”
phenomenon, which affects the addressing accuracy. There-
fore, in order to increase the cognitive ability and
search range of particles, PSO algorithm is improved. As-
suming that variable $a$ is the storage vector, for a particle $i$,
select a particle $j$ arbitrarily, and the storage vector can be
expressed as [14]
\[
\theta = p_{i,d} - x_j,
\]
where $x_j$ is the position of particle $j$ at the same time.

Add the storage vector to the addressing process of
particles, improve the update strategy of particles, expand
the search scope of particles, and solve the problem of “too
early maturity.” The update strategy is [15]

\[
v_{i,d}(t + 1) = \begin{cases} 
\omega [v_{i,d}(t) + c_1 r_1 \theta + c_2 r_2 (p_{g,d}(t) - x_{i,d}(t))] \\
\omega [v_{i,d}(t) + c_1 r_1 (p_{i,d}(t) - x_{i,d}(t)) + c_2 r_2 (p_{g,d}(t) - x_{i,d}(t))] 
\end{cases}
\]

depends on gradient information, avoids the requirements of
gradient descent method on function, shortens the
training time of neural network, and greatly improves the
search efficiency.
The fusion of IPSO algorithm and BP algorithm is
mainly reflected in two aspects. Firstly, the position vector of
particles in IPSO algorithm will correspond to all connection
weights and thresholds of BP algorithm and find the optimal
position through fitness function, that is, find the optimal
weight and threshold of BP network. Secondly, the forward
Propagation theory of BP neural network is used to calculate the particle fitness, and the particle fitness function is defined according to the trained mean square error \([16]\). The training steps of IPSO-BP neural network are as follows:

1. By analyzing the sample data, the BP network model is constructed.

2. Input training data to determine the fitness function value of each particle.

3. Parameter initialization: assign values to each parameter.

4. Update the velocity and position of the particle swarm according to formulas (7)–(10).

5. Iterative operation: if the current fitness value is better than the local optimal value of particle swarm optimization, it will be replaced to update the local optimal solution of particle swarm optimization.

6. The global optimal position vector is mapped to the weight and threshold of BP neural network.

7. Input the samples to be predicted into the optimized network model and analyze the prediction results.

The specific process is shown in Figure 3.

4.3. Training Results and Analysis. In order to verify the scientificity of the teaching quality evaluation index system and the reliability of IPSO-BP model, 2000 pairs of input and output data are randomly generated by the program between \([0,1]\) on the MATLAB platform as training samples, and the data are trained by BP neural network and IPSO-BP neural network, respectively.

This paper adopts a three-layer BP neural network framework. There are 16 nodes in the output layer, 5 nodes in the hidden layer, and 1 node in the output layer.

In the process of setting model parameters, the calculation formula of particle dimension is

\[
D = I \times H + H \times O + H + O,
\]

(11)

where \(I\) is the number of neurons in the input layer; \(H\) is the number of neurons in the hidden layer; and \(O\) is the number of neurons in the output layer.

Calculate the particle dimension according to formula (11), \(D = 16 \times 5 + 5 \times 1 + 5 + 1 = 11\). Because the number of particles has a great impact on the final optimization results, if it is too small, the search range is limited, the optimization accuracy is low, and the "premature" problem is easy to occur. If it is too large, the algorithm is complex, which will greatly reduce the optimization efficiency. Therefore, in this paper, the number of particles is taken as \(N = 60\). The maximum number of iterations is 500. The learning factor is as follows: \(C_1 = 1.5, C_2 = 2\). The maximum and minimum values of inertia weight are 0.8 and 0.3, respectively. The speed range is \([-1, 1]\). The transfer function of neurons in hidden layer and output layer is sigmoid function, and Trainig function is used for network training. The target error of the network is 0.001. When the training error is less than the target error, the training ends. The results are shown in Figures 4 and 5.

Mean square error (MSE), prediction accuracy, training time, and iteration times are used as evaluation performance indicators for analysis and compared with the BP model. The results are shown in Table 2.

It can be seen that compared with BP neural network model, the IPSO-BP model has fast convergence speed and can find the optimal solution in less iterations. At the same time, the training error of the model is small, and a better prediction accuracy can be obtained. The training results...
Table 2: Comparison of training results.

| Model       | Running time (s) | Accuracy (%) | MSE     | Number of iterations |
|-------------|------------------|--------------|---------|----------------------|
| BP model    | 24.08            | 85.8         | 0.0927  | 364                  |
| IPSO-BP model | 8.95            | 96.2         | 0.0613  | 243                  |

Table 3: Evaluation grade division.

| Grade       | Excellent | Good | Medium | Pass | Fail |
|-------------|-----------|------|--------|------|------|
| Value range | 0.90~1.00 | 0.80~0.89 | 0.70~0.79 | 0.60~0.69 | 0~0.59 |
show that the IPSO-BP neural network model has certain reliability and effectiveness and can be used to evaluate the quality of classroom teaching.

5. Teaching Quality Evaluation Based on IPSO-BP Neural Network Model

5.1. Evaluation Grade Division. According to the expert experience and the actual situation of the course teaching effect, the evaluation results are divided into five levels, namely, "excellent, good, medium, pass, and fail," and the value range of each level is specified, as shown in Table 3.

5.2. Collection of Sample Data. In order to construct the sample data needed in the training process of IPSO-BP neural network model, six professional courses of animal science major of Inner Mongolia University for Nationalities from 2020 to 2021 are selected as the object of teaching quality evaluation, the comprehensive score of the attendance results of school supervisors is taken as the expected output, and the questionnaire score results of students in class are taken as the training data. In order to reduce the demand of the network for samples, firstly, the training results need to be normalized to keep the results between [0, 1]. The normalization calculation formula is

\[ z = \frac{x - \min(x_i)}{\max(x_i) - \min(x_i)} \]  

(12)

Table 4: Evaluation results of experts in each course and the number of questionnaires.

| Course name          | Number of questionnaires | Expert evaluation results | Expert evaluation score |
|----------------------|--------------------------|---------------------------|-------------------------|
| 《Animal anatomy》    | 35                       | Excellent                 | 0.93                    |
| 《Animal physiology》 | 38                       | Good                      | 0.86                    |
| 《Animal nutrition》  | 43                       | Medium                    | 0.77                    |
| 《Animal genetics》   | 40                       | Good                      | 0.84                    |
| 《Animal reproduction》 | 36                      | Excellent                 | 0.94                    |
| 《Feed science》      | 30                       | Good                      | 0.87                    |

Table 5: Training results of some samples.

| Course name          | Sample number | Actual output | Expected output | Training results | Expert results |
|----------------------|---------------|---------------|-----------------|------------------|----------------|
| 《Animal anatomy》    | 1             | 0.9523        | 0.95            | Excellent        | Excellent      |
|                      | 2             | 0.9486        | 0.95            | Excellent        | Excellent      |
|                      | ...           | 35            | 0.9535          | Excellent        | Excellent      |
| 《Animal physiology》 | 1             | 0.8482        | 0.85            | Good             | Good           |
|                      | 2             | 0.8627        | 0.85            | Good             | Good           |
|                      | ...           | 38            | 0.8545          | Good             | Good           |
| 《Animal nutrition》  | 1             | 0.776         | 0.75            | Medium           | Medium         |
|                      | 2             | 0.7486        | 0.75            | Medium           | Medium         |
|                      | ...           | 43            | 0.7683          | Medium           | Medium         |
| 《Animal genetics》   | 1             | 0.8369        | 0.85            | Good             | Good           |
|                      | 2             | 0.8454        | 0.85            | Good             | Good           |
| 《Animal reproduction》 | 1            | 0.9317        | 0.95            | Excellent        | Excellent      |
|                      | 2             | 0.9532        | 0.95            | Excellent        | Excellent      |
|                      | ...           | 36            | 0.9478          | Excellent        | Excellent      |
First of all, experts are invited to evaluate the listening results of six professional courses: Animal anatomy, Animal physiology, Animal nutrition, Animal genetics, Animal reproduction, and Feed science. Secondly, a questionnaire is distributed to students to examine the teaching effect of each course, so as to obtain sample data. Then, the IPSO-BP neural network model is trained by using the sample data of the first five courses, and the model is optimized according to the expert evaluation results. Finally, the trained model is used to test and evaluate the last course to test the effectiveness of the evaluation model. A total of 222 valid samples were received in the questionnaire. The first 192 samples were used for the training of IPSO-BP neural network model, and the last 30 results were used for the test of network generalization ability. The evaluation results of experts in each course and the number of questionnaires are shown in Table 4.

5.3. Evaluation Results and Analysis. Input 192 sample data of the first five courses into IPSO-BP network model for training and complete the training after approaching the evaluation index. The training results of some samples are shown in Table 5.

In Table 5, taking the teaching quality evaluation results of Animal anatomy course as an example, among the evaluation indicators, “innovative ability training (A_{32})” has the best evaluation results, and the indicator “teaching ideas (A_{32})” has poor evaluation results and needs to be improved in this regard, but the overall evaluation grade is “excellent.”

In order to further discuss the effectiveness of IPSO-BP neural network model, the modeling time and evaluation accuracy in the evaluation process are graphically represented and compared with BP neural network and PSO-BP neural network, as shown in Figures 6 and 7.

The results show that compared with the other two models, the IPSO-BP neural network model has fast modeling speed and can greatly reduce the network running time. At the same time, the accuracy rate of the teaching
quality evaluation of the model is more than 94%, while the accuracy rate of the BP model is the least, less than 85%. It shows that IPSO algorithm can not only solve the "premature" phenomenon of PSO algorithm but also effectively optimize the weight and threshold of neural network, so as to improve the performance of BP algorithm and meet the application requirements of teaching quality evaluation.

5.4. Testing and Verification. The purpose of model training is application, so it is necessary to test the trained model to verify the generalization ability of the trained network model. 30 data samples of "Feed science" course are tested in the trained IPSO-BP neural network model and compared with the BP neural network model. The test results of some samples are shown in Table 6.

In order to analyze the test results more intuitively, the results in Table 6 are represented by curves, as shown in Figures 8 and 9.

It can be seen that among all 30 test samples, the IPSO-BP neural network model has 29 samples with correct judgment, only one sample has wrong judgment, and the evaluation accuracy is 96.7%, while BP neural network model has 4 samples with wrong judgment, and the evaluation accuracy is 86.7%. The test results show that the IPSO-BP neural network model constructed in this paper can greatly improve the prediction accuracy and has strong generalization ability. It can obtain better evaluation results when it is used in the evaluation of teaching quality.

6. Conclusions

(1) Aiming at the problems of BP neural network, an IPSO-BP neural network model is constructed. The improved particle swarm optimization algorithm is used to optimize the weight and threshold of neural network, so as to improve the performance of BP algorithm. The simulation results show that the model has the advantages of fast operation speed and high addressing accuracy.

(2) Taking teaching attitude, teaching content, teaching method, and teaching effect as indicators, the teaching quality evaluation index system is established. Taking the animal science major of Inner Mongolia University for Nationalities as an example, the sample set is constructed, and the IPSO-BP neural network model is used for sample training and testing.

(3) The results show that compared with other models, the IPSO-BP neural network model has fast convergence speed, good robustness, 96.7% prediction accuracy, and strong generalization ability. At the same time, it further verifies the effectiveness of the established evaluation index system and provides a new way for teaching quality evaluation.

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 conflicts of interest.

Acknowledgments
This study was supported by the Inner Mongolia Autonomous Region of Science and Technology Innovation Guiding Project (KCB[201802]) (2022 Basic Scientific Research Business Expense Project of Colleges and Universities Directly under the Inner Mongolia Autonomous Region: Leading Scientific and Technological Talents and Innovative Team Building (Young Top Talents Cultivation Project)).

References

[1] J. Yang and Z. Shao, “Fragility and countermeasure analysis of teaching quality evaluation mechanism in ethnic region,” Journal of Research on Education for Ethnic Minorities, vol. 32, no. 05, pp. 150–158, 2021.

[2] X. Shen, Research on Quality Evaluation of Online and Offline Mixed Teaching of Advanced Mathematics a Based on Neural Network, Yangtze University, Jingzhou, China, 2021.
[3] F. Zhou, “On fuzzy comprehensive evaluation of teaching quality of mathematics courses in colleges and universities,” Studies in College Mathematics, vol. 24, no. 1, pp. 24–27, 2021.

[4] Y. Fan and L. Ma, Research on Evaluation Model of Teaching Quality in Colleges and Universities Based on Grey System Theory, University Education, no. 2, pp. 185–188, China, 2019.

[5] X. Zhao, Y. Zhou, and L. Qu, “Construction of MOOC teaching quality evaluation index system for College Physics,” Journal of Southeast University (Philosophy and Social Science), vol. 19, pp. 163–168, 2017.

[6] Li Wu and Y. Liu, "On teaching quality evaluation based on support vector machine and evidence theory." Journal of South China Normal University (Social Science Edition), vol. 41, no. 2, pp. 92–98, 2016.

[7] M. Yao, I. J. L, and Q. Wang, "Prediction of college students' performance based on BP neural network," Journal of Jilin University (Engineering and Technology Edition), vol. 39, no. 4, pp. 451–455, 2021.

[8] H. Li, J. Chen, and X. Zheng, "Construction of evaluation index system of classroom teaching quality in Colleges and Universities," China Continuing Medical Education, vol. 12, no. 17, pp. 85–87, 2020.

[9] Y. U. E Qi and W. E. N. Xin, "A research on evaluation model of teaching quality based on BP neural network and genetic algorithm," Journal of Inner Mongolia University (Natural Science Edition), vol. 49, no. 2, pp. 204–211, 2018.

[10] L. A. N. Song and J. Huang, "Design of teaching quality evaluation model based on BP neural network," Mechanical & Electrical Technology, vol. 35, no. 5, pp. 31–33, 2020.

[11] Y. Zheng and Y. Chen, "Research on evaluation model of university teachers' teaching quality based on BP neural network," Journal of Chongqing University of Technology: Natural Science, vol. 29, no. 1, pp. 85–90, 2015.

[12] M. Xu and S. Wang, "Application of PSO optimized neural network in teaching quality evaluation [J]," Computer Engineering and Design, no. 20, pp. 5327–5329, 2008.

[13] J. Xin, "Improved neural network-based teaching quality evaluation of university physics experiment [J]," Modern Electronics Technique, vol. 40, no. 15, pp. 146–149, 2017.

[14] F. Qian, Multi Objective Optimization Based on Improved Particle Swarm Optimization and its Application, University of Science and Technology Beijing, Beijing, China, 2022.

[15] J. Zhang, R. Jin, and W. Wang, "Research and practice of university mechanical laboratory safety evaluation model based on IPSO-BP neural network," Research and Exploration in Laboratory, vol. 39, no. 12, pp. 290–296, 2020.

[16] Q. Fan, W. Shi, and A. Liao, "Reliability evaluation of vehicles based on grey comprehensive evaluation and PSO-BP," Journal of Railway Science and Engineering, vol. 19, no. 1, pp. 239–247, 2022.