

Research Article

An Improved Genetic Algorithm and Neural Network-Based Evaluation Model of Classroom Teaching Quality in Colleges and Universities

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Research on educational quality has gotten a lot of attention as the current higher education teaching reform continues to deepen and grow. The key to improving education quality is to improve teaching quality, and teacher evaluation is an important tool for doing so. As a result, educational management requires the development and refinement of a system for evaluating teaching quality. Traditional approaches to assessing teaching quality, on the other hand, are problematic due to their limitations. As a result, a scientific and reasonable model for evaluating the teaching quality of college undergraduate teachers must be developed. We present a unique model for evaluating the quality of classroom teaching in colleges and universities, which is based on improved genetic algorithms and neural networks. The basic idea is to use adaptive mutation genetic algorithms to refine the initial weights and thresholds of the BP neural network. The teaching quality evaluation findings were improved by improving the neural network's prediction accuracy and convergence speed, resulting in a more practical scheme for evaluating college and university teaching quality. We have conducted simulation experiments and comparative analysis, and the mean square error of the results of the proposed model is very low, which proves the effectiveness and superiority of the algorithm.

1. Introduction

The goal of teaching quality evaluation [1–4] is to promote teaching reform, improve teaching quality, reduce student burden [5–7], develop students' intelligence [8], and help students evaluate and solve problems. We must achieve the unity of ideology, science, and feasibility when evaluating the quality of teaching, and we must do so in an objective, fair, and rational manner, rather than subjectively guessing or mixing personal feelings [9, 10]. In colleges and universities, teaching quality is often assessed through four channels: student evaluation, expert evaluation, peer evaluation, and instructor self-evaluation, with the final evaluation results

synthesized. However, certain issues remain in the process of developing, utilizing, and evaluating the teaching quality assessment system's evaluation outcomes [3, 4], such as evaluation theory research [11], evaluation method usage, evaluation method update, and evaluation data analysis. These issues have a direct impact on educational institutions. In the future, quality assessment and knowledge extraction will be critical [12].

The indicators in the evaluation system generally involve teaching attitude [13], proficiency in teaching content, and basic teaching skills [14–16], etc. However, the comprehensive quality of teachers is not only reflected in the above aspects but also includes teachers' knowledge level, teaching

research ability, teaching design ability, and teachers' innovation ability, etc. But at present, these evaluation indexes which can fully reflect the comprehensive quality and personality of teachers are seldom involved in the evaluation system, so they should be fully considered in the establishment of the evaluation index system.

The indicators in the evaluation system [17] of the differences in the degree of influence of the evaluation results should be assigned different weights, but many colleges and universities still use the same weight method, or subjectively determined a weight distribution table to establish the evaluation system, and then use this evaluation system to evaluate. Therefore, the reasonable allocation of weight is the key step to perfect the evaluation system.

Teaching quality and teaching quality evaluation systems must be synchronized in colleges and universities; the current situation necessitates the construction of a teaching quality evaluation system; its positioning determines for teachers that teaching quality evaluation cannot be done solely through the theory of teaching evaluation; more attention must be paid to the cultivation of students. They can also address the needs of social development in the real world. As a result, assessing teaching quality is an important aspect of teaching management. We will use intelligent technology to make the evaluation of teaching quality more scientific and quantitative based on the above knowledge. At the same time, the study content of this paper serves as a diagnosis, feedback, and incentive, allowing for the early detection of difficulties in the teaching process and timely feedback to teachers in order to improve and improve teaching quality. Furthermore, scientific evaluation will apply appropriate pressure to teachers, motivating them to actively enhance the quality of their instruction and talent development.

The following are the main innovation points of this paper:

- (1) This research develops a model for evaluating college classroom teaching quality based on an improved genetic algorithm and a neural network, resulting in a novel way for evaluating college teaching quality. At the same time, it is expected to provide a valuable reference basis for the teaching management department to obtain scientific teaching quality evaluation work plans and programs, as well as provide reasonable judgments for the promotion and evaluation of teachers' professional titles, and make teaching management more scientific, institutionalized, and standardized
- (2) This research uses an adaptive mutation genetic technique to optimize the BP neural network's initial weights and thresholds. Because the BP neural network's initial weights and threshold value are so critical, utilizing a better genetic algorithm to optimize the initial weights and threshold value, reduce the BP neural network's training duration to satisfy the weight termination conditions and time threshold, and increase the neural network's teaching quality to the prediction accuracy assessment findings

2. Related Work

2.1. Genetic Algorithm. The basic idea of genetic algorithm [18–20] is to simulate the evolutionary process of the population, which is to conduct organized random information exchange and recombination for individuals [21, 22]. In the string structure of the previous generation, adaptive bits and segments are selected to recombine to generate a new generation of population, namely, "survival of the fittest." As an additional addition, occasionally, new bits and segments are added to the string structure to replace the original ones, known as "mutations." After the three genetic operations of selection, crossover, and mutation, the population is constantly updated, the population's good degree is constantly enhanced, and the global optimal solution is approached. The process of the standard genetic algorithm is shown in Figure 1.

2.2. BP Network. Compared with the other intelligent models [23], the back propagation neural network, also known as the feedforward neural network [24-26], is a very simple prediction model, and it has a three-layer feedforward hierarchical network with input, hidden, and output layers [27, 28]. The topology of the three-layer feedforward neural network is shown in Figure 2. When a set of input modes is presented to the network, the BP network will learn the set of input modes in the following order: first, the hidden layer unit receives the input mode from the input layer. An input mode is generated and delivered to the output layer after the hidden layer unit processes the input mode layer by layer. Forward propagation is the term for this phenomenon. The output findings are then compared to the predicted values. If the expected values are not met, error back propagation is used. Error signals are decreased by altering the connection weights of neurons at each layer, and the error is returned along the original path. As part of a "memory training" process, forward propagation and back propagation alternate. The system repeats these two stages, learning until the difference between the output value and the expected value is within a certain range, at which point the system stops learning. The fresh sample is now fed into the trained network, and the associated output value is calculated.

For the hidden layer, there are

$$y_{i} = f(net_{i}), j = 1, 2, \cdots, m,$$
 (1)

$$\operatorname{net}_{j} = \sum_{i=0}^{n} v_{ij} x_{i}, j = 1, 2, \cdots, m,$$
(2)

where f(x) is

$$f(x) = \frac{1}{1 + e^{-x}},$$
 (3)

$$f'(x) = f(x)[1 - f(x)].$$
 (4)

When the network output is not equal to the expected



FIGURE 1: Schematic diagram of genetic algorithm.



FIGURE 2: Schematic diagram of genetic algorithm.

output, the output error *E* exists, which is defined as follows:

$$E = \frac{1}{2} (d - o)^2 = \frac{1}{2} \sum_{k=1}^{l} (d_k - o_k)^2.$$
 (5)

Expand the above error definition to the hidden layer, then:

$$E = \frac{1}{2} \sum_{k=1}^{1} \left[d_k - f(\operatorname{net}_k) \right]^2 = \frac{1}{2} \sum_{k=1}^{1} \left[d_k - f\left(\sum_{j=0}^{m} W_{jk} Y_j \right) \right]^2.$$
(6)

It can be seen from the above formula that the network input error is a function of the weights w_{jk} and v_{ij} of each layer, so adjusting the weights can change the error *E*. Obviously, the principle of adjusting the weight is to continuously reduce the error, so the adjustment of the weight should be proportional to the negative gradient of the error, that is,

$$\Delta w_{jk} = -\eta \frac{\partial E}{\partial w_{jk}},\tag{7}$$

$$\Delta v_{ij} = -\eta \frac{\partial E}{\partial v_{ii}}.$$
(8)

The negative sign in the equation represents the gradient descent, and the constant $\eta \in (0, 1)$ represents the proportional coefficient, which reflects the learning rate during training. It can be seen that the BP algorithm belongs to the δ learning rule class.

3. Methodology

3.1. Adaptive Mutation Genetic Algorithm. The calculation equation of adaptive mutation probability *P* is as follows:

$$P = \frac{(P_1 + P_2)}{2} = \frac{\left((P_0(P_0 - P_{\min}) * m/M) + (P_0 * \max F(X_K)/\bar{F}) \right)}{2},$$
(9)

where *M* is the maximum evolutionary algebra, *m* is the current evolutionary algebra, P_1 is inversely proportional to the evolutionary algebra, P_2 is inversely proportional to the average fitness value, P_0 is the assumed initial mutation probability, P_{\min} is the minimum value of the mutation probability range, and \bar{F} is the average fitness value of the current group, which is the maximum fitness value of the current group.

3.2. Adaptive Mutation Genetic-BP Model

3.2.1. Network Construction. All continuous functions can be mapped using a feedforward neural network with a single hidden layer. Two hidden layers are only required for learning discontinuous functions. As a result, a multilayer feedforward neural network requires no more than two hidden layers. In general, the initial step in creating a multilayer feedforward neural network is to create a hidden layer. If the hidden layer has a big enough number of nodes and the network performance does not improve, the training cost will rise as the number of hidden layers grows. As a result, this post tries to employ a hidden layer initially. Because the input layer gets data from the outside, the number of nodes is determined by the size of the problem's input vector. The transfer function used by the input layer is generally a linear function, that is, f(x) = x. The trial-and-error method is one of the methods to determine the number of hidden layer nodes. After this procedure has found the initial value, experiments can be carried out by raising the number from small to small and analyzing the outcomes to identify the best number. The trial and error approach has three ways to determine the initial value, and the calculation equation is as follows:

$$m = \sqrt{n+l} + \alpha, \tag{10}$$

$$m = \log 2^n. \tag{11}$$

3.2.2. Adaptive Mutation Genetic Algorithm. A genetic algorithm's goal is to find network weights and thresholds that minimize the network's sum of squared errors over all evolutionary generations, while the fitness function evolves in the direction of increasing its value, making the fitness function the inverse of each individual learning error. The following are the learning error and fitness function calculation equations:

$$E = \frac{\sum_{k=1}^{p} \sum_{j=1}^{l} \left(y_{j}^{k} - o_{j}^{k} \right)}{2}, \qquad (12)$$

fitness =
$$\frac{1}{E}$$
, (13)

where *E* is the learning error, *p* is the number of training samples that is 2000 sets of evaluation data, *l* is the number of output nodes 1, and $y_j^k - o_j^k$ is the error of the *k*-th sample relative to the *j*-th output node.

The mutation operation is the process by which the genes of some people in a population mutate with a certain probability. The adaptive mutation probability mutation operation is used in the model. Although bad individual shapes will appear to some extent, the genetic operation method of mutation will retain some favorable mutations, increase the diversity of the genetic algorithm population, and cause it to jump out of the local optimal solution in time, search for the global optimal solution, and avoid premature phenomena.

3.3. Teaching Quality Evaluation Model. First, by analyzing existing problems in teaching quality evaluation, we can improve them and establish a more complete and more appropriate index system. Collect teaching quality evaluation sample data, select evaluation indicators according to the teaching characteristics of teachers, and divide the collected teaching quality evaluation data into training samples and test samples. Second, determine the learning rate, the number of hidden layer neurons, the maximum number of iterations, the minimum error accuracy, the transfer function, the number of training, and other parameters of the BP neural network method. By inputting samples into the evaluation model, iterative training is continuously carried out until the triggering algorithm stops. Then, for teaching quality evaluation, enter the test sample to see if the training impact of the enhanced genetic algorithm-optimized BP neural network model fulfills the requirements. Enter the next phase if the prediction result meets the stop criteria; otherwise, return to the previous stage and retrain the network. Finally, to obtain the teaching quality evaluation result, input the sample into the teaching quality evaluation model.

4. Experiments and Results

4.1. *Experimental Environment*. The experimental system software environment used in this article is shown in Table 1.

When updating parameters, lr means the learning rate is 0.0001. The experiments with all the algorithms were performed on a computer equipped with a single NVIDIA GTX1080 GPU (8 GB).

4.2. Data Collection. Teaching quality evaluation consists of four parts: leader evaluation, expert evaluation, peer evaluation, and student evaluation. The methods of obtaining teaching quality evaluation data are as follows: (1) Leadership Evaluation. Take random lectures and evaluate the teacher's teaching and student learning. (2) Expert Evaluation. The Academic Affairs Office and each college will determine the evaluation courses, respectively, and the expert group will conduct inspection courses. (3) Peer Evaluation. Organize experienced teachers to evaluate peer teachers and adopt the methods of listening, evaluating, and discussing lectures to improve the teaching strategies and methods of the assessed teachers and improve their teaching ability. (4) Student Evaluation. Every semester, students evaluate the teaching quality of their own class teachers. Teachers' teaching quality evaluation is usually arranged in the middle of the semester and before the final exams in each semester. Our data set consists of 2 data from different universities, named Data1 and Data2, respectively.

4.3. *Evaluation Index.* We use the mean square error to evaluate the proposed algorithm, and its calculation equation is as follows:

$$MSE = \frac{1}{mp} \sum_{p=1}^{p} \sum_{j=1}^{m} \left(y \wedge_{pj} - y_{pj} \right)^2,$$
(14)

TABLE 1: Parameters of the experimental environment.

Туре	Parameter
OS	Windows 10
CPU	Intel Core I5
RAM	8.00 GB
Development tools	Pycahrm

TABLE 2: Comparison of the results of the experiment on Data1.

Sample number	BP		Ours	
	Prediction	MSE	Prediction	MSE
1	11.02	7.25%	10.23	5.22%
2	15.62	6.12%	16.21	4.36%
3	14.20	5.26%	14.69	4.12%
4	11.98	6.21%	12.01	5.36%
5	12.17	4.31%	13.01	3.33%
6	12.36	6.25%	11.98	4.11%

TABLE 3: Comparison of the results of the experiment on Data2.

Sample number	ВР		Ours	
	Prediction	MSE	Prediction	MSE
1	10.03	7.15%	11.24	5.11%
2	16.11	6.31%	15.99	5.08%
3	13.11	5.11%	13.89	3.93%
4	10.19	6.32%	11.88	4.99%
5	12.33	3.89%	11.09	4.11%
6	12.12	5.91%	11.23	3.99%

where *m* is the number of output nodes, *p* is the number of training samples, \hat{y}_{pj} is the expected output value of the network, and y_{pj} is the actual output value of the network. Compared with the standard BP neural network error, the reduction of the output error of other samples will not directly lead to the increase of iteration times after the weight modification. The setting of cumulative error is to reduce the global error of the whole training set, rather than the error of a specific small sample. Therefore, the mean square error is more reasonable than the cumulative error.

4.4. *Experimental Results*. The results of the training of the teaching quality evaluation model based on the proposed method and the traditional BP method are compared, and the results are shown in Tables 2 and 3.

Compared with the prediction results of the traditional BP algorithm for 6 groups of samples, the error between the output value of the teaching effect measured by our method and the real value is relatively small. To see if BP neural network has better approximation ability and more accurate prediction effect based on improved genetic algorithm and neural network of institutions of higher learning in classroom teaching quality evaluation model of ability to predict on the teaching quality evaluation prediction, thus, more scientific and accurate evaluation of college teaching quality and teaching effect showed the effectiveness of the



FIGURE 3: Mean square error of the proposed method and BP on Data1.



FIGURE 4: Acc of the proposed method and BP on Data1.



FIGURE 5: Loss of the proposed method and BP on Data1.

model. Figures 3 and 4 also show the MSE and ACC comparison curve during the training process, and Figure 5 shows the training loss curve.

5. Conclusion

In recent years, improving the quality of higher education teaching has been a top concern, and teacher evaluation is an important measure of educational and instructional quality. As a result, educational administration requires the development and refining of a system for measuring teaching quality. Traditional teaching quality evaluation approaches, on the other hand, have been rendered ineffective due to their limitations. As a result, a scientific and fair teaching quality evaluation model must be developed to assess the teaching quality of college undergraduate teachers. We present a unique approach for measuring the quality of classroom teaching in colleges and universities, which is based on improved genetic algorithms and neural networks. The basic idea is to use adaptive mutation genetic algorithms to modify the initial weights and thresholds of the BP neural network. Because the BP neural network's initial weight and threshold are so crucial, the improved genetic algorithm is used to optimize the BP neural network's initial weight and threshold in order to reduce the time it takes for the BP neural network to find the weight and threshold that meets the training termination condition. Improving the neural network's prediction accuracy and convergence speed to the teaching quality evaluation findings resulted in a more practical scheme for evaluating college and university teaching quality.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

All the authors do not have any possible conflicts of interest.

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