Prediction and Management of the Quality of Classified Student Training Based on an Improved Neural Network

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Abstract—Personalized teaching and classified training promote each student to develop in the most suitable direction. The studies on classified student training (CST) mainly target the objects of CST, which refers to the classified training of underachievers and achievers, or the classified training of different groups of high-quality talents like doctoral students and master candidates. However, there are few research results on the implementation or quality forecast of CST. To fill up the gap, this paper explores the prediction and management of the CST quality based on an improved neural network. Firstly, a cognitive diagnosis model for CST was established to realize targeted group learning. Thereafter, an evaluation index system (EIS) was constructed for student learning quality. Next, a prediction model was built based on improved backpropagation neural network (BPNN), and the particle swarm optimization (PSO) was called to optimize the weights and thresholds of the neural network. The effectiveness of our model was proved through experiments. The relevant findings provide impetus to the timely update of CST.

Keywords—classified student training (CST), backpropagation neural network (BPNN), learning quality, prediction and management

1 Introduction

College education nowadays primarily aim to enhance the overall quality of students, and enable every student to realize the optimal development. But this universal aim is not equal to setting up a unified development standard for all students [1-8]. Despite facing all students, effective college education does not deny the fact that students vary in learning ability and cognitive state [9-15]. To promote each student to develop in the most suitable direction, it is necessary to start from the personalized features of students, and implement personalized teaching and classified training [16-19]. Therefore, a re-examination of the current value of classified student training (CST) would help to develop future college education and new teaching models.

As more and more teachers combine their courses with online learning, crowdsourcing tutoring has proven to effectively improve the CST quality. Prihar et al. [20] found that crowdsourcing tutoring benefits the personalized training of students, allowing many teachers to create more pertinent teaching contents for different learning groups, and demonstrated that the teaching content effectiveness of crowdsourcing tutoring varies with the knowledge level of students. Aiming to determine the role of teachers in personalized development of higher education college students in northern India, Upadhayay et al. [21] prepared a questionnaire on the students' evaluation of the roles, attitudes, behaviors, knowledge, and skills of college/institution teachers, and tried to reveal how these factors affect the students' personalized development and performance. In order to improve the learning efficiency of students, Liu and Zhang [22] proposed a gray-based learning curve prediction method to determine the number of practical opportunities for knowledge ingredients. The experimental results show that, compared with learning factor analysis, their method outputs a predicted learning curve close to the actual learning curve, judging by the practical opportunity error rate on the knowledge ingredient. Therefore, their method provides a reasonable tool for personalized teaching. Different students may contact different educational programs. Their possible learning situations can be evaluated by big data applications. Regan and Jesse [23] defined the relevant courses as personalized learning, and identified six ethical issues: information privacy, anonymity, monitoring, autonomy, nondiscrimination, and information ownership, and discussed the ethical and policy aspects of personalized learning. Zulkifli et al. [24] reviewed the literature on the implementation of learning among undergraduate teams, investigated the influence of personality type and learning style over the learning process, and explored the relevant themes in the field of information system. Guided by Okoli's system evaluation method, they carried out systematical evaluation of the datasets of Scopus, ScienceNet.cn, and Association for Information Systems (AIS).

Domestically speaking, the studies on CST mainly target the objects of classified training, which refers to the classified training of underachievers and achievers, or the classified training of different groups of high-quality talents like doctoral students and master candidates. Considering the influence of CST over the applicable courses, some scholars also carried out group teaching in view of the different knowledge features of different disciplines and courses. However, there are few research results on the implementation or quality forecast of CST. Therefore, this paper explores the prediction and management of the CST quality based on an improved neural network. Section 2 establishes a cognitive diagnosis model for CST, and realizes targeted group learning. Section 3 sets up an evaluation index system (EIS) for student learning quality, builds a prediction model on improved backpropagation neural network (BPNN), and calls the particle swarm optimization (PSO) to optimize the weights and thresholds of the neural network. The effectiveness of our model was proved through experiments. The relevant findings provide impetus to the timely update of CST.

2 Cognitive diagnosis model for CST

The cognitive diagnosis model can accurately describe the personalized features of each student, making it possible to organize pertinent group learning and prepare corresponding learning plans, in the light of the subtle difference between students in cognitive state. The learning plans covers how to recommend learning materials of the suitable difficulty, according to the cognitive state of students in each group, how to arrange the learning progress of each group, according to the background knowledge and learning ability of students in each group, and how to predict the CST quality, according to the current learning paths of students in each group.

The cognitive states of students can be depicted by a fuzzy cognitive diagnosis model. Figure 1 presents the construction flow of cognitive diagnosis model, which can judge the cognitive states of students based on their test scores, as well as the expert evaluations of the correspondence between test questions and knowledge points in courses. The traditional fuzzy cognitive diagnosis model often judges the objective questions in student tests, and its prediction of student cognitive states is usually discrete. The proposed model makes a fuzzy diagnosis of student cognitive states, according to the test scores collected from online education platforms or educational administration system, as well as the correspondence between test questions and knowledge points in courses. The diagnosis results fall within the interval of [0, 1].

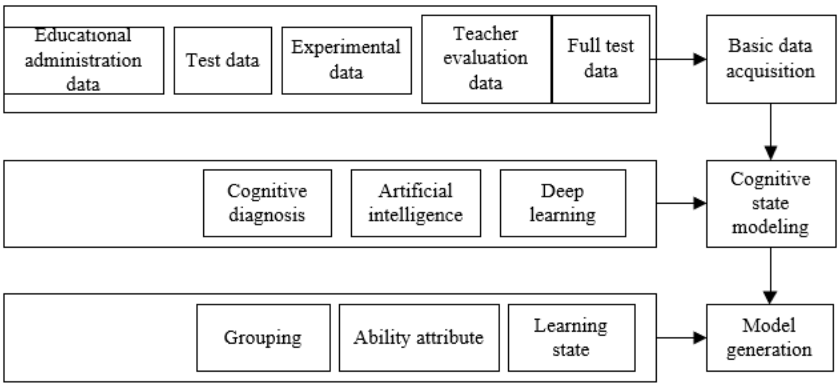


Fig. 1. Construction flow of cognitive diagnosis model

Let δ_{in} be the potential response of student E_i at cognitive state φ_i in test U_n. The value of δ_{in} depends on the cognitive state of the student and the knowledge points covered by the test. Let φ_i be the vector of knowledge point mastery of student E_i; W_n be the vector of knowledge points covered in test U_n; $\varphi_i \cdot W_n$ be the overall mastery of student E_i for the knowledge points covered in test U_n; $\|W_n\|$ be the norm of W_n. Then, δ_{in} can be defined as:

$$\delta_{in} = \frac{\phi_i \cdot W_n}{\|W_n\|^2} \tag{1}$$

Let h_n and e_n be the guessing parameter and error parameter of each test U_n, respectively. Both parameters affect the test scores of each student, which is assumed to obey the Gaussian distribution. Let $M(P_{im}|[(1\text{-}\delta_{in})\times h_n+\delta_{in}\times(1\text{-}e_n)], \varepsilon^2{}_n)$ be the probability density function of the Gaussian distribution with a mean of $(1\text{-}\delta_{in})\times h_n+\delta_{in}\times(1\text{-}e_n)$, and a variance of $\varepsilon^2{}_n$; P_{in} be the scores of student E_i in test U_n; $\varepsilon^2{}_n$ be the normalized variance of the scores in test U_n. Suppose student E_i belong to the cognitive state of φ_i. Then, the probability to obtain scores P_{in} in test U_n can be calculated by:

$$R\left(E_i,U_n\right)=R\left(P_{in}\mid\phi_i\right)=M\left(P_{in}\mid\left[\left(1-\delta_{in}\right)\times h_n+\delta_{in}\times\left(1-e_n\right)\right],\varepsilon_n^2\right) \tag{2}$$

The parameters of the cognitive diagnosis model were estimated by Markov Chain Monte-Carlo (MCMC) algorithm. It is assumed that $v(0, 1)$ is uniformly distributed. Let $\beta(a, b, min, max)$ be the beta distribution of the four parameters in $[min, max]$, with a and b being shape factors; $\Phi(x, y)$ be the gamma distribution with a shape factor of e and a scale factor of ε. In the actual teaching environment, the prior distribution of the parameters of the cognitive diagnosis model can be given by:

$$\begin{aligned}
&\phi\sim v\left(0,1\right)\\
&e\sim\beta\left(a_e,b_e,min_e,max_e\right)\\
&h\sim\beta\left(a_h,b_h,min_h,max_h\right)\\
&\frac{1}{\varepsilon^2}\sim\Phi\left(x_\varepsilon,y_\varepsilon\right)
\end{aligned} \tag{3}$$

Based on the score matrix P, the joint posterior probability of parameters φ, e, h, and ε^2 can be given by:

$$R\left(\phi,e,h,\varepsilon^2\middle|P\right)\propto K\left(\phi,e,h,\varepsilon^2\right)R\left(\phi\right)R\left(e\right)R\left(h\right)R\left(\varepsilon^2\right) \tag{4}$$

Let M_U be the number of tests; M_E be the number of students. The likelihood function $SR(\varphi, e, h, \varepsilon^2)$ of the cognitive diagnosis model can be defined as:

$$SR\left(\phi,e,h,\varepsilon^2\right)=\prod_{n}^{M_U}\prod_{i}^{M_E}M\left(P_{in}\mid\left[\left(1-\delta_{in}\right)\times h_n+\delta_{in}\times\left(1-e_n\right)\right],\varepsilon_n^2\right) \tag{5}$$

For the given score matrix P, the conditional distribution probabilities of parameters φ, e, h, and ε^2 can be respectively given by:

$$R\left(\phi\mid P,e,h,\varepsilon^2\right)\propto SR\left(\phi,e,h,\varepsilon^2\right)R\left(\phi\right) \tag{6}$$

$$R\left(e,h\mid P,e,h,\varepsilon^2\right)\propto SR\left(\phi,e,h,\varepsilon^2\right)R\left(e\right)R\left(h\right) \tag{7}$$

$$R\left(\varepsilon^2\mid P,\phi,e,h\right)\propto L\left(\phi,e,h,\varepsilon^2\right)R\left(\varepsilon^2\right) \tag{8}$$

Figure 2 shows the execution flow of our model.

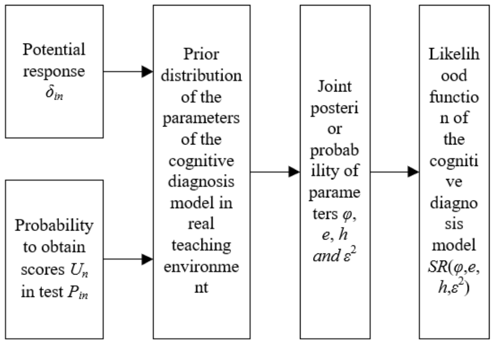


Fig. 2. Execution flow of our model

3 CST quality prediction

Figure 3 shows the structure of EIS for student learning quality, which underpins our CST quality evaluation. It can be observed that the EIS covers two major aspects: One is the indices of student learning ability, i.e., the manifestation of student ability; the other is the statistical indices of student cognitive state.

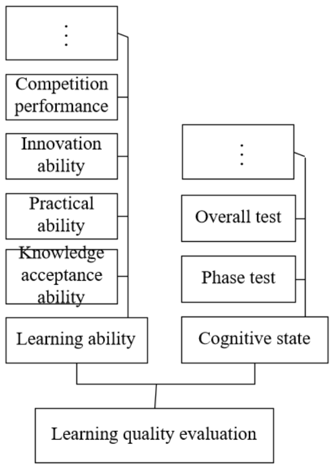


Fig. 3. Structure of EIS for student learning quality

Figure 4 illustrates the structure of the CST quality prediction system. All index data were collected from the current and new platforms, including the educational administrative system, online learning platforms, smart mobile terminals (apps), and course resource libraries.

Since CST quality changes through the training, the prediction of CST quality is a time series prediction problem in supervised learning. This paper improves the BPNN to build a prediction model, and optimizes the weights and thresholds of the BPNN through PSO.

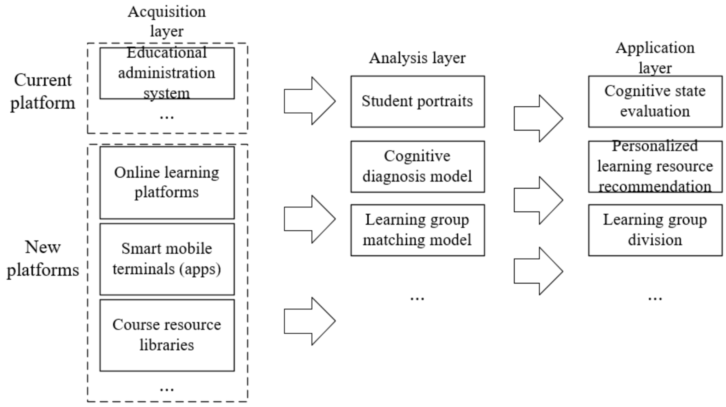


Fig. 4. Structure of the CST quality prediction system

Let k, N, and T be the input, hidden, and output layer nodes, respectively; i be the i-th node; m be the sample size; A_l=[a_1, a_2, a_3, …] and B_l=[b_1, b_2, b_3, …] be the actual input and output vectors, respectively; O_l=[o_1, o_2, o_3, …] be the ideal output vector; θ_{ij} be the connection weight between the i-th input layer node and the j-th hidden layer node; λ_j be the threshold of the j-th hidden layer nodes; β_{jf} be the connection weight between the j-th hidden layer node and the f-th output layer node; λ_f be the threshold of the f-th output layer node; δ and σ be the learning step length and preset gradient error, respectively. Then, the learning of our neural network can be summarized as follows:

Step 1. Initialize the thresholds and weights of the BPNN, i.e., randomly assign the values of the parameters in (-1, 1).

Step 2. Randomly extract a set of CST quality samples, and import them into the BPNN as an input vector.

Step 3. Let $g(a)$=1/1+e^{-a} be the s-shaped transfer function g; E_j be the output of the input layer; Y_j be the output of the hidden layer. Based on the input vector, connection weight θ_{ij}, and threshold λ_j, compute the output of each layer in the network in the forward direction by:

$$E_j = \sum_{i=1}^{m} \theta_{ij} A_j - \lambda_j \tag{9}$$

$$Y_j = g\left(E_j\right) \tag{10}$$

Derive the output K_l of each node from Y_j, β_{jf}, and λ_f. Compute the output B_f of every output layer node by:

$$K_l = \sum_{j=1}^{m} \beta_{jf} Y_j - \lambda_f \tag{11}$$

$$B_f = g\left(K_l\right) \tag{12}$$

Step 4. Compute the network prediction error based on the actual output vector B_f and ideal output vector O_l. Define this error s as the quadratic sum of the differences between B_f and O_l:

$$s=\frac{1}{2}\Sigma\left(B_f-O_l\right)^2 a \tag{13}$$

Step 5. Based on the general error of the network, revise the weights and thresholds of each layer of the BPNN to realize the backpropagation. Let $\partial s/\partial a$ be the gradient of formula (13) in the l-th operation relative to thresholds or weights; $a(l)$ be the threshold vector or weight vector of the l-th operation. By fixing the step length, compute the weights and thresholds:

$$a\left(l+1\right)=a\left(l\right)-\delta\times grad \tag{14}$$

Let ρ be the number of trainings; φ be the momentum coefficient; S be the error function; δ be the learning rate. Adjust the weights by:

$$\Delta q\left(\rho+1\right)=-\delta\frac{\partial S}{\partial q}+\phi\Delta q\left(\rho\right) \tag{15}$$

Let $x_{ij}(m)$ be the momentum term. Improve the update speed by:

$$\frac{\partial S^*}{\partial q_{ij}}\left(m\right)=\frac{\partial S}{\partial q_{ij}}\left(m\right)+decay\times q_{ij}\left(m\right) \tag{16}$$

Let $h(m)$ be the gradient direction of the error curve. In the m-th learning, obtain the search direction $SO(m)$ by:

$$SO\left(m\right)=-h\left(m\right)+\frac{\left\|\nabla h\left(m\right)\right\|^2}{\left\|\nabla h\left(m-1\right)\right\|^2}\left(m-1\right) \tag{17}$$

It is assumed that, in the PSO, the particle swarm has N particles, each of which contains C-dimensional attribute information. The dimensionality equals the number of parameters of the neural network to be optimized. Let $\vec{a}=(a_1, a_2, ..., a_C)$ and $\vec{u}=(u_1, u_2, ..., u_C)$ be the position vector and speed vector of each particle, respectively, forming a set of solutions to the parameter optimization problem of the neural network. Let $u^{\rho+1}_{i,j}$ be the update of speed component of the i-th particle in the direction of the j-th parameter after the ρ-th iteration, and q be the inertial weight; λ_1 and λ_2 be learning factors; SJ_1 and SJ_2 be two random numbers in [0, 1]; $P^i_B(i, j)$ be the optimal position of the i-th particle relative to the j-th parameter after the ρ-th iteration, i.e., the local optimal value; $G^i_B(i, j)$ be the optimal position of the swarm after the ρ-th iteration, i.e., the global optimal value. Then, the PSO process aims to update the position vector and speed vector of particles iteratively:

$$\begin{cases} u_{i,j}^{\rho+1} = qu_{i,j}^{\rho} + \lambda_1 SJ_1 \left(P_B^{\rho}\left(i,j\right) - q_{i,j}^{\rho} \right) + \lambda_2 SJ_2 \left(G_B^{\rho}\left(i,j\right) - a_{i,j}^{\rho} \right) \\ a_{i,j}^{\rho+1} = a_{i,j}^{\rho} + u_{i,j}^{\rho} \\ i = 1,2,...,N, \ j = 1,2,...,C \end{cases} \tag{18}$$

Let L be the number of classes of the samples; V be the number of CST quality samples in a class; a be the position vector of a sample; λ_j be the position vector of class center. Then, the criterion function of the PSO can be expressed as:

$$H = \sum_{j=1}^{L} \sum_{v \in V} \left(a_v - \lambda_j \right)^2 \tag{19}$$

The traditional PSO only uses P_B and G_B. With the aid of clustering algorithm, this paper classifies the topology of unfixed swarms in the PSO to realize the mutual learning between particles in the swarm. Let m_B be the optimal parameter in the cluster; $m^{\rho}{}_B(i, j)$ be the position vector of the optimal particle in the cluster after the ρ-th iteration; λ_3 be the learning factor of the neighborhood; p_3 be a random number in the interval [0, 1]. Then, formula (18) can be revised into:

$$\begin{cases} u_{i,j}^{\rho+1} = qu_{i,j}^{\rho} + \lambda_1 SJ_1 \left(P_B^{\rho}\left(i,j\right) - a_{i,j}^{\rho} \right) + \lambda_2 SJ_2 \left(G_B^{\rho}\left(i,j\right) - a_{i,j}^{\rho} \right) \\ +\lambda_3 SJ_3 \left(m_B^{\rho}\left(i,j\right) - a_{i,j}^{\rho} \right) \\ a_{i,j}^{\rho+1} = a_{i,j}^{\rho} + u_{i,j}^{\rho} i = 1,2,...,N, \ j = 1,2,...,C \end{cases} \tag{20}$$

Let PD^{ρ} be the diversity of the swarm after the ρ-th iteration; $\bar{a}^{\rho}{}_j$ be the mean of the swarm in the j-th dimension. The swarm diversity can be calculated by:

$$\begin{cases} PD^{\rho} = \sum_{i=1}^{N} \sqrt{\sum_{j=1}^{C} \left(a_{i,j}^{\rho} - \bar{a}_j^{\rho} \right)^2} \\ \bar{a}_j^{\rho} = \frac{1}{N} \sum_{i=1}^{N} a_{i,j}^{\rho} \end{cases} \tag{21}$$

The swarm momentum, which characterizes the ability of particles searching for the local optimum, can be calculated by:

$$L_S = \sum_{i=1}^{N} \sum_{j=1}^{C} \frac{\left(a_{i,j}^{\rho} \right)^2}{2} \tag{22}$$

The flow of the prediction model is given in Figure 5.

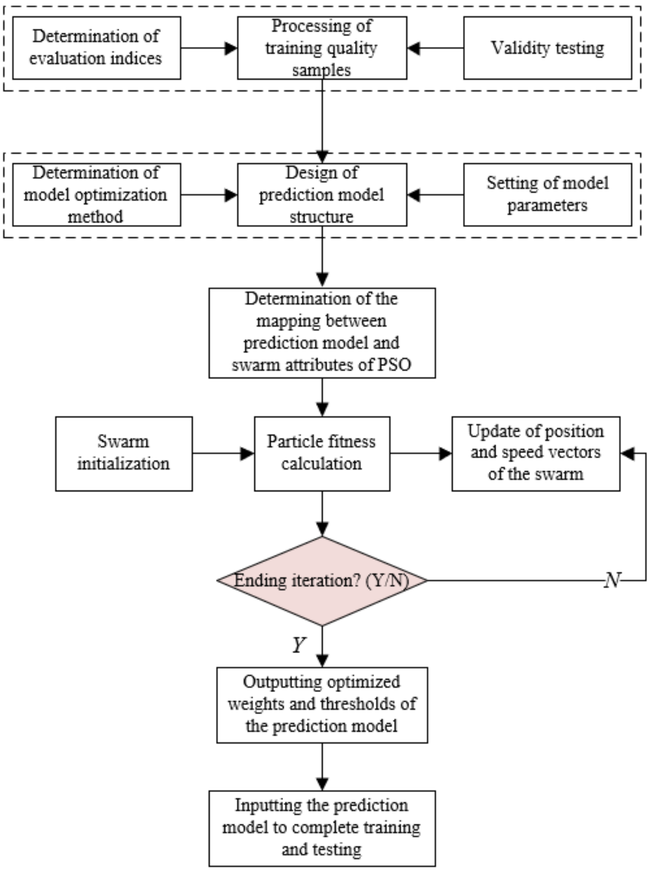


Fig. 5. Flow of the prediction model

4 Experiments and results analysis

Figures 6 and 7 provide the convergence curves and experimental results of our prediction model, respectively. It can be seen that the post-clustering PSO converged to the global optimal point faster than the pre-clustering PSO, i.e., the clustering improves the optimization ability substantially. The relative error between predicted CST quality and the actual value was within 15%. The high prediction accuracy proves that our algorithm is applicable to CST quality prediction.

The training quality of each student depends on the weights of the EIS for student learning quality. The CST quality reflects the overall influence of grouping on overall student ability. Here, the students are divided into groups by three different methods: learning ability-based method, learning method-based method, and learning attitude-based method. Then, the three grouping methods were compared with the proposed learning cognition-based grouping through experiments. Figure 8 compares the CST qualities of the four approaches. It can be seen that the mean CST quality increased in every grouping method, and our method realized the most stable growth, which is slightly better than the other methods. With the growing number of groups, the CST quality variance of our method declined, greatly reducing the gap between students. Meanwhile, the CST quality variances of the other methods were on the rise, for they only consider high-performance students.

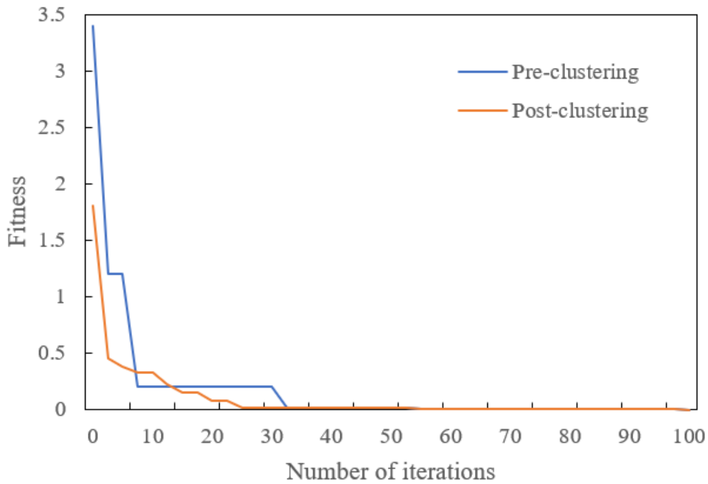


Fig. 6. Convergence curves of the prediction model

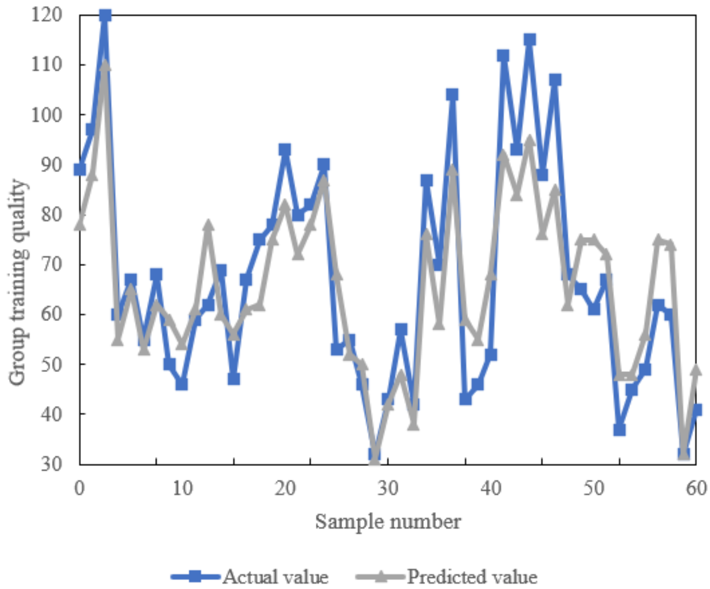
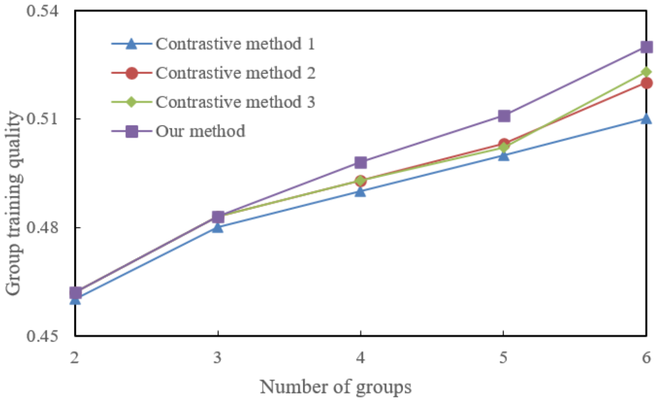
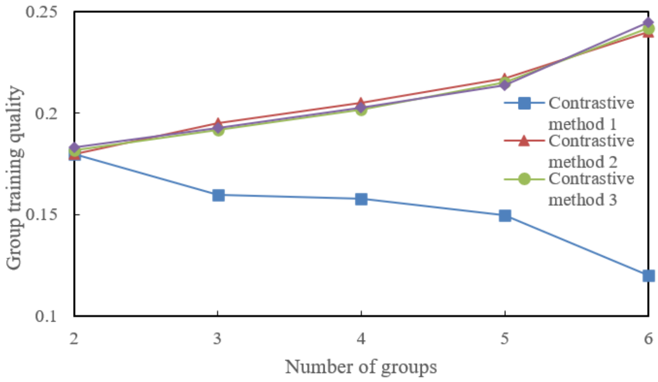


Fig. 7. Experimental results of our prediction model



(1)



(2)

Fig. 8. Comparison of CST qualities of different methods

Furthermore, the student participation in group learning activities was examined from different dimensions of CST quality. Table 1 compares the CST quality increments through group learning.

In Table 1, all increments were positive, suggesting that Grade 4 students are all better trained than Grade 3 students. The post-group learning CST quality was higher than the pre-group learning CST quality in terms of knowledge acceptance ability, practical ability, innovation ability, competition performance, phase test scores, and overall test scores. When it comes to the mean CST quality, the post-group learning level was much higher than the pre-group learning level in terms of practical ability, innovation ability, phase test scores, and overall test scores, and slightly higher than the latter in knowledge acceptance ability, and competition performance. Overall, the students are more likely to access suitable learning resources and contents, and better trained, after grouping learning.

Table 1. Comparison of mean CST qualities before and after group learning

Observation point	Class	Grade 3	Grade 4	Increment	Difference
1	Pre-grouping	2.6158	3.2615	0.6457	0.1262
	Post-grouping	2.6257	2.8414	0.2157	
2	Pre-grouping	3.0251	3.2670	0.2419	0.1518
	Post-grouping	2.5584	2.7495	0.1911	
3	Pre-grouping	3.6292	3.8146	0.1854	-0.0748
	Post-grouping	3.2686	3.4180	0.1494	
4	Pre-grouping	3.1748	3.6289	0.4541	0.1925
	Post-grouping	2.7481	2.9357	0.1876	
5	Pre-grouping	2.8116	3.6205	0.8089	0.3692
	Post-grouping	2.3147	2.8154	0.5007	
	Pre-grouping	2.7485	3.0152	0.2667	
6	Post-grouping	3.3157	3.6295	0.3138	0.1528
	Pre-grouping	2.8475	3.1629	0.3154	

5 Conclusions

This paper explores the prediction and management of the CST quality based on an improved neural network. Firstly, a cognitive diagnosis model for CST was established to realize targeted group learning, and an EIS was constructed for student learning quality, paving the way to pertinent group learning. Next, a prediction model was built based on improved BPNN, and the PSO was adopted to optimize the weights and thresholds of the neural network. After that, the convergence curves and experimental results of our prediction model were presented, which prove the feasibility of the proposed algorithm in CST quality prediction. Then, the CST qualities of different grouping methods were compared through simulation. The comparison shows that the CST quality variance of our method was falling, greatly reducing the gap between students. Finally, the mean CST qualities before and after group learning were compared, further confirming the effectiveness of our model.

6 Acknowledgment

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