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Article

Application of Improved BP Neural Network in Predicting Teaching Effectiveness of Information Literacy Education in Colleges and Universities

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Abstract: This paper takes the evaluation of teaching effect of information literacy education in colleges and universities as the research object, and establishes the evaluation index system of teaching effect of information literacy education, which includes 13 first-level indexes and 30 second-level indexes in the four dimensions of students' information consciousness, information application, information ethics, and information ability. The BP neural network improved by particle swarm optimization algorithm is used to establish a mathematical model for evaluating the teaching effect of information literacy, which uses the BP model trained by PSO to fit the complex relationship between the many indicators affecting the evaluation of the teaching effect of information literacy in colleges and universities and the evaluation results. Through the data research on undergraduates of University D and training analysis using the research data, it is concluded that the training error of PSO-BP algorithm is stabilized at less than 0.02 after 5000 steps of training, and the training time of the model is 10 s. The BP neural network improved by the PSO algorithm is more stable than the pre-improvement connection weight learning process and achieves the ideal error accuracy faster, and its predicted output value is basically in line with the expected value. Its predicted output value is basically consistent with the expected value. The evaluation results also show that the information literacy education in School D needs to be strengthened in terms of information awareness and information application. It shows that the PSO-BP model can be used to effectively predict the effectiveness of information literacy teaching in colleges and universities.

Keywords: BP neural network; PSO-BP; particle swarm optimization algorithm; information literacy; teaching effect evaluation

1. Introduction

Information literacy education in colleges and universities, as the process of empowering individuals to effectively search, select and evaluate information resources, is not only the training of students in skills such as information retrieval, but also the cultivation of a higher level of competence and quality of survival in the information society, which involves information awareness, information competence, media literacy, information ethics, and lifelong learning [1-4]. Information literacy education is a multidisciplinary and comprehensive education involving multiple disciplines such as integrated educational technology, library and intelligence, psychology, ethics and information technology, which cannot be accomplished through a single course and a few trainings, not to mention simple techniques and methods [5-7]. Therefore, effective prediction of the teaching effect of information literacy education is of great significance for the cultivation of college students' information literacy.

The traditional methods of predicting teaching effectiveness are mainly based on the teacher's prediction based on students' daily performance, study time, etc., whose subjectivity and the dynamics of students' performance make the prediction results inaccurate [8-9]. And with the continuous development of artificial intelligence technology, neural network has become one of the most popular machine learning models [10], BP neural network is one of the most classic one, which provides technical support for the prediction of the teaching effect of information literacy education in colleges and universities [11-12]. BP neural network is a nonlinear adaptive dynamic system, which consists of a large number of processing units with powerful learning ability, memory ability as well as computational ability and intelligent processing [13-14]. However, traditional BP networks have problems such as slow training speed and easy overfitting. In the prediction of teaching effect of information literacy education in colleges and universities, in order to enhance the generalization ability of BP neural network, improve the training speed, enhance the convergence of the network, and improve the prediction accuracy, based on the improvement of BP neural network has become an important direction of the current neural network research [15-16].

Teaching effectiveness evaluation is one of the key points in teaching research, but the existing mathematical evaluation model is not suitable for solving nonlinear problems, and the neural network model has slow convergence speed and low accuracy. Aiming at the above problems, this paper proposes an evaluation index system of information literacy in colleges and universities that contains 13 first-level indicators and 30 second-level indicators in four dimensions, and forms a scientific, effective and easy-to-use PSO-BP neural network evaluation model.

The model uses PSO particle swarm optimization algorithm to calculate the initial connection weights and thresholds of the BP neural network, so as to improve the global optimization ability of the model and the convergence speed and accuracy. The questionnaire was designed according to the established information literacy evaluation index system, and the data research was conducted on the students of University D to obtain the evaluation data. And the evaluation results of PSO-BP and other different algorithms are compared with the actual values to verify the prediction accuracy of the proposed PSO-BP evaluation model, which provides a new method and approach for evaluating the teaching effect of information literacy education in colleges and universities.

2. Evaluation index system of information literacy teaching effect in colleges and universities

Research on the evaluation of information literacy mainly focuses on the four dimensions of information awareness, information knowledge, information ability and information ethics. Information literacy of students in colleges and universities is extended on this basis, requiring undergraduate vocational education students to be able to clarify the information they need for their own learning, to effectively judge whether the information is conducive to solving real-world problems, and to have the ability to communicate and share information with the outside world through diversified information channels. Accelerating the construction of information literacy standards for students promotes the comprehensive development of students' information literacy, cultivates a group of “great nation craftsmen” with high information literacy for the country, and thus realizes the goal of quality education in the era of education informatization 2.0.

2.1. Test methods

Systematically combing the key indicators of the research related to students' information literacy and combining the new connotation of information literacy in the era of education informatization 2.0, the evaluation index system of information literacy of vocational education undergraduates is preliminarily constructed. At the same time, based on the principles of scientificity, comprehensiveness, accuracy and operability, the expert survey method was applied to solicit opinions twice from experts in colleges and universities and research organizations. It took 6 months to collect 21 revised opinions from 8 experts in information literacy related fields. In this process, through several revisions of the evaluation indicators of information literacy of university students, the evaluation indicator system covering 4 fields, 13 primary indicators and 29 secondary indicators was finally constructed, and the weights of each indicator were determined through the expert assignment method.

2.2. System of evaluation indicators

The evaluation index system constructed in this study mainly consists of 13 first-level indicators in four major fields, covering the indicators of the four major fields of information awareness, information application, information ethics, and information competence, which is able to test the degree of students' own mobility in a pluralistic society and meet the needs of students' personal development and social progress. The evaluation index system of information literacy of college students is shown in Table 1.

Table 1. Student information literacy evaluation index system

dimension	Primary indicator	Secondary indicator
Information awareness	Information requirements(A1)	Be able to clearly identify the information needed for one's own learning(B1)
		Be able to describe the types and characteristics of the information one needs(B2)
	Information sensitivity(A2)	Sensitivity to surrounding information(B3)
		Sensitivity to professional information(B4)
	Information awareness(A3)	Recognize the value and role of information(B5)
		Recognize the timeliness of information(B6)
Information application	Information mastery(A4)	Understand the basic knowledge of information and information technology(B7)
		Master the knowledge of integrating information with work and life(B8)
		Master the knowledge of promoting one's own development through information(B9)
	Information applications(A5)	Utilize information to provide corresponding references for learning(B10)
		Utilize information to provide support for corresponding work(B11)
Information ethics	Information ethics(A6)	Understand the relevant laws and regulations concerning the use of information(B12)
		Understand the recognized moral standards and behavioral norms in the information society(B13)
	Information ethics behavior(A7)	Ethics of Information Acquisition(B14)
		Ethics of Information Use(B15)
		Ethics of Information Exchange(B16)
	Information security ethics(A8)	Understand information security laws and regulations(B17)
		Possess common sense of information security(B18)
		Maintain the information security of others(B19)
Information ability	Information acquisition ability(A9)	Make use of web search engines(B20)
		The ability to conduct information retrieval through means such as libraries(B21)
		The ability to identify the retrieved information(B22)
	Information creation ability(A10)	The ability to integrate and reorganize old information(B23)
		The ability to integrate new information into a new knowledge system(B24)
	Information evaluation capability(A11)	Judge whether the information is true and reliable(B25)
		Effectively judge whether the information is conducive to solving practical problems(B26)
	Information sharing ability(A12)	Information communication sharing ability with the outside world through diversified information channels(B27)
		The ability to communicate and share information with other groups, teachers, friends and other groups(B28)
	Information management capability(A13)	The ability to classify, store, and collect information according to information(B29)
		The ability to process and handle information as needed(B30)

3. Evaluation model of information literacy teaching effect based on PSO-BP

3.1. BP neural network fundamentals

Artificial neural network is an algorithm by which people simplify and simulate biological neural network systems through mathematical and theoretical methods. One of the most widely used artificial neural network algorithms is the back propagation network (BP neural network).

BP network has input layer, hidden layer and output layer.The operation process of BP neural network is mainly divided into two parts: forward propagation of information and backward propagation of error. When the information that has been obtained from the input layer input, the input layer contains multiple neurons, and then use the association between the layer and the layer down to the hidden layer, and then down to the output layer, the process of each node's weights and thresholds will not change, the process is known as the forward propagation of information; when the output layer to get the output value, with the actual value of the substitution of the loss function, through the gradient descent method, respectively, to the hidden layer and the output layer in the Thresholds and weights are adjusted, the process is called the backward propagation of error. The parameters in the network are continuously adjusted until the output error value is in an acceptable range.The steps of the BP neural network algorithm are shown in Figure 1.

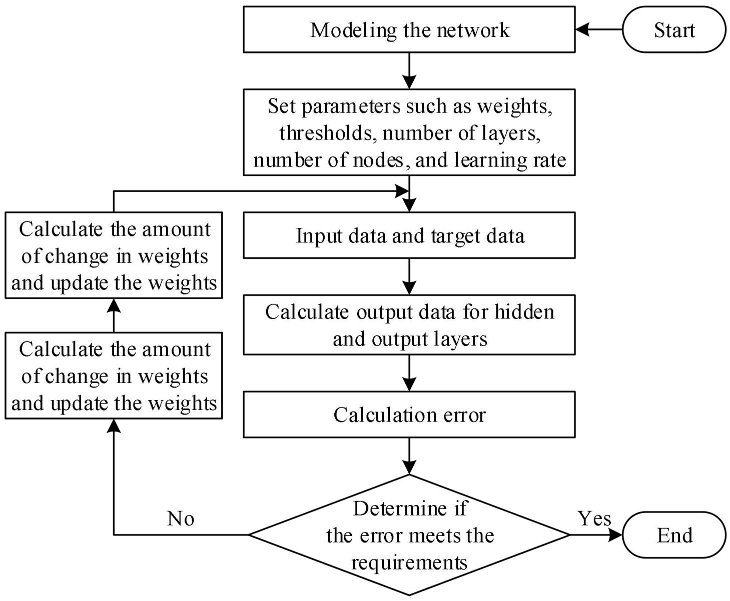

Figure 1. Flow chart of BP neural network algorithm

3.2. Principles of Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) is an algorithm model established by the study of bird feeding behavior, and then improved to form a group intelligence optimization algorithm. Bird flocks can always hunt for food through group information sharing i.e. the first bird in the flock to find more food will cause the flock to search for food in its vicinity, and the range will be narrowed down until the food source is found, and its correspondence is shown in Table 2.

Table 2. Bionic correspondence table of PSO algorithm

Bird feed	**PSO**
Bird	Alpha particle
Forest	Solution space
Food quantity	Objective function value
Position of each bird	A solution to space (particle position)
Position with the largest amount of food	Global optimal solution

The optimal position of each particle after searching itself in the current situation is denoted as P_{best} (particle best), and the optimal position among the P_{best} of all particles in the population is denoted as G_{best} (global best). The particle will change its velocity and position information according to the current P_{best} of the particle itself and the G_{best} of the whole population. After the change, the adaptation values of all particles in the current space need to be calculated again to update P_{best} and G_{best}.

The essence of the algorithm is to iteratively update the information of each particle in the current particle swarm in the set space, and stop iterating when the optimal information is found, so the current speed and position of the particles in the space are affected by three factors, i.e., inertia of the particles themselves, P_{best} and G_{best}. The specific process is shown in Figure 2.

The position finding formula of the particle is:

$$x_{id+1} = x_{id} + v_{id+1} \tag{1}$$

The formula for calculating the velocity of a particle is:

$$v_{id+1} = \omega v_{id} + c_1 r\left(p_{id} - x_{id}\right) + c_2 r\left(p_{gel} - x_{id}\right) \tag{2}$$

where: x_{id}, v_{id} are the position and velocity of the i th particle in d -dimensional space, respectively; ω is the inertia weight factor; γ is the randomly generated number from 0 to 1; c is the acceleration factor; p_{id} is the current optimal position; and p_{gd} is the global optimal position.

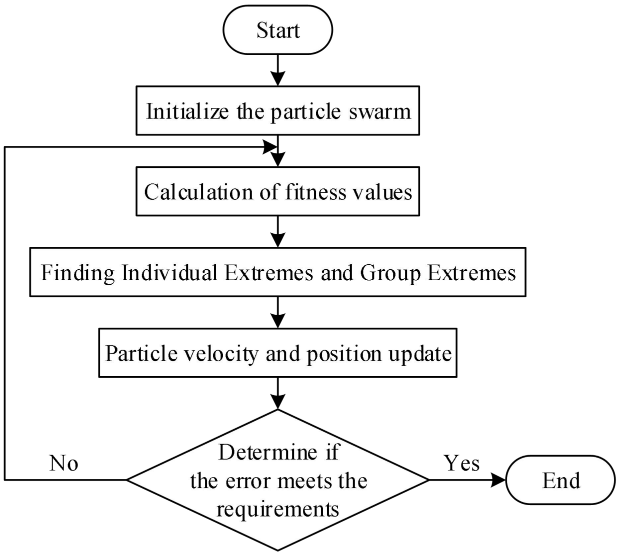

Figure 2. Flow chart of PSO algorithm

3.3. Creation of PSO-BP algorithm

As the BP neural network often shows certain limitations in the implicit layer calculation process, the calculation efficiency will be greatly reduced. The particle swarm algorithm can efficiently avoid the gradient descent phenomenon in BP neural network computation and effectively reduce the BP neural network implicit layer computation time. Mainly because the learning process of BP neural network is mainly the process of constant optimization of weights and thresholds, the position of different particles in the PSO algorithm corresponds to the calculation of weights and thresholds one by one, and the output error of the neural network is used as the judgement adaptation function of the PSO algorithm. The optimization search of PSO algorithm is used to train the weights and thresholds of the neural network.PSO algorithm replaces the gradient descent method of BP algorithm to train the weights and thresholds of the neural network, which can significantly improve the computational performance of the BP neural network, and fundamentally avoid the problem of BP neural network falling into a local minimum in the process of calculating the sample training set, which improves the generalization performance of the neural network algorithm.

The flow of PSO-BP neural network algorithm is shown in Figure 3 as follows:

Step 1. Form the BP neural network topology with 19 teaching quality evaluation indicators, and determine the initial weights and thresholds of the 19 evaluation indicators in the BP neural network.

Step 2. Initialization of particle swarm algorithm parameters: Establish the particle population of the 19 indicators and determine the initial values of the particle dimensions, learning factors, inertia weights, maximum number of iterations, speed and position.

Step 3. Select the appropriate fitness function and calculate the fitness value for each particle (evaluation indicator).

Step 4. Analyze the reasonable value of the fitness of each particle (evaluation index) given to find the individual particle optimal position (Pbest) and the global optimal position (gbest) of the particle.

Step 5. Update the velocity and position of the particle according to the velocity and position update formula.

Step 6. Return to step 4 when the number of iterations does not exceed a set maximum number of iterations, and end the iteration if it is greater than the maximum number of iterations.

Step 7. Assign the optimal solution calculated by the particle swarm, i.e., the optimized optimal weights and thresholds, to the BP neural network, and carry out research data learning and training.

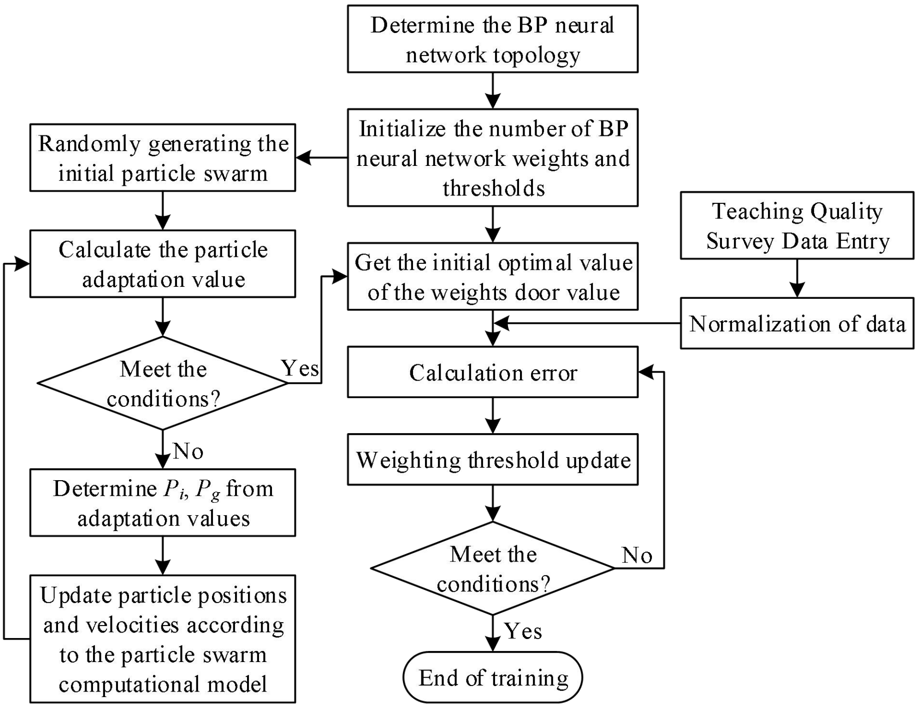

Figure 3. PSO-BP algorithm flowchart

4. Experimental results and analysis

4.1. Data collection and pre-processing

Undergraduates of the class of 2021 majoring in civil engineering, mining engineering and engineering mechanics of University D were selected as the survey respondents. The questionnaire was designed as a Likert scale for the evaluation of information literacy teaching quality indexes, and relying on the platform of Questionnaire Star, the questionnaire was sent to the surveyed students by stratified sampling method, so that the students could complete the questionnaire independently and review the validity. A total of 1,342 questionnaires were collected, and 1,200 valid questionnaires were obtained after screening, totaling 1,200 sets of valid data. Since the difference in magnitude between the data has a large impact on the prediction accuracy and convergence effect of the model, the input data were normalized before modeling. The PSO-BP algorithm was used to evaluate the teaching effect and reasonably predict the effect of information literacy education teaching in this school.

4.2. Model training

The preprocessed dataset is divided into training set and test set according to the ratio of 4:1, the teaching quality evaluation index data as 10 neurons in the input layer of BP neural network, and the predicted evaluation results as the output. According to Kolmogrov theory: any given continuous function can be precisely realized by a three-layer neural network, this paper chooses a single hidden layer and adopts a three-layer network structure.

The number of neurons in the hidden layer is determined to be 15 after several trials using empirical formulas and the trial-and-error method, and the activation function is chosen to be a sigmoid function. The output layer consists of five neurons, corresponding to the evaluation results: excellent, good, medium, passing and failing, and the activation function of the output layer adopts softmax function. The loss function is the mean square error (MSE). During the training process, the initial random number weight matrices of each layer of the BP neural network are expanded into a horizontally aligned one-dimensional matrix, and the resulting matrix is used as the particle input to the PSO algorithm.The loss function of the BP neural network is used as the fitness function of the PSO. Each iteration reorganizes the weights in the particles into connected weight matrices of the BP neural network and trains them in order to compute the obtained fitness values and update the velocity and position of the particles until the conditions are satisfied and the updating is stopped.

4.3. Model training results

Simulation experiments are realized using Python language under Ubuntu 16.04 operating system with hardware configuration of RAM 8 GB, CPU lntel Core i7-6700HQ, GPU NVIDIA GeForce GTX 1060.The change of training error is shown in Fig. 4, and the goodness-of-fit curve of prediction results is shown in Fig. 5. From Fig. 4, it can be seen that when the number of training steps is 5000 steps, the training error curve stably maintains below 0.02, and the model training time is 10s, which is a short training time and high training efficiency. From Fig. 5, it can be seen that the output value predicted by the model is basically consistent with the expected value, indicating that the model has good approximation effect and high prediction accuracy.

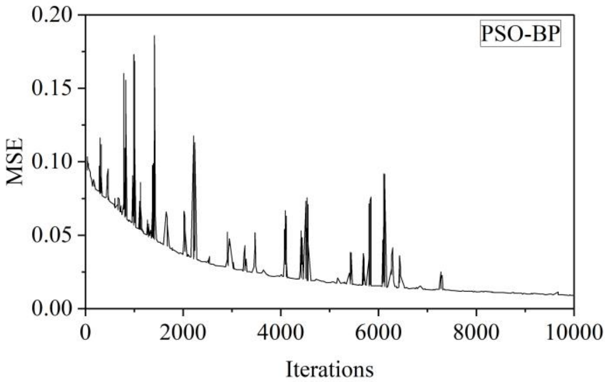

Figure 4. Training error curve

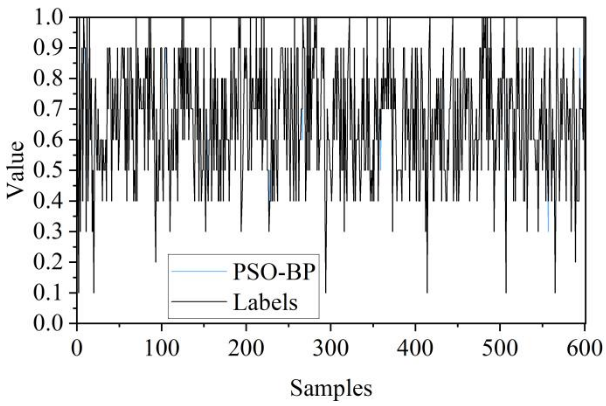

Figure 5. Fitting curve

4.4. Comparative analysis

4.4.1. BP Neural Network Before and After Improvements

In this paper, the BP neural network model is optimized, and the PSO algorithm is introduced on the basis of the BP neural network, which aims to improve the speed of convergence of the network connection weights and ensure that the learning process will not diverge. A series of experiments are conducted to verify the convergence results of the BP network connection weights after the introduction of momentum as shown in Figure 6.

The general BP network connection weights are adjusted greatly, and the oscillation trend is more obvious; while the optimized BP network connection weights of PSO algorithm are more stable in the learning process, and there is no large fluctuation. This verifies the stability of PSO-BP network connection weight convergence.

In addition, allowing the BP neural network to adaptively adjust the learning rate during training can improve the network training speed, the effect is shown in Figure 7. The general BP neural network reaches the ideal error accuracy slowly, and there has been an oscillation during the training process. The PSO-BP neural network convergence speed is faster, and the pre-adaptive adjustment of the learning rate fast global optimization, to find the optimal solution after the iteration is basically stable and unchanged. Comparison experiments verify the stability and efficiency of the optimized BP neural network of PSO algorithm.

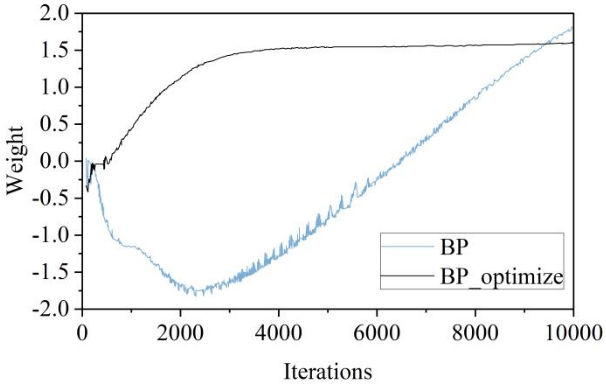

Figure 6. Network connection weighting convergence

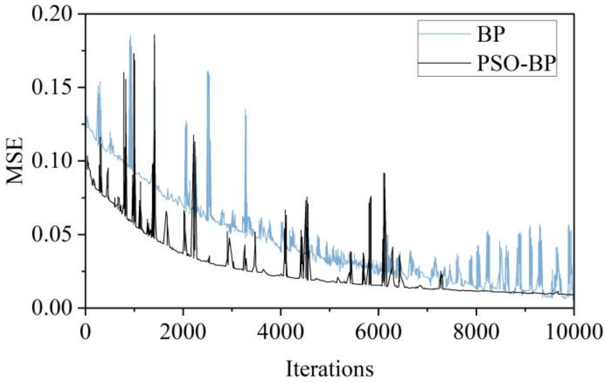

Figure 7. Loss function changes

4.4.2. Comparison of other models

The trained model is tested with the remaining 1/5 data, and the effect is shown in Figure 8. The predicted values of the evaluation results are basically consistent with the real scores, and the PSO-BP model is able to make a scientific and accurate evaluation of the quality of information literacy teaching in colleges and universities, and the model's generalized reasoning ability is strong.

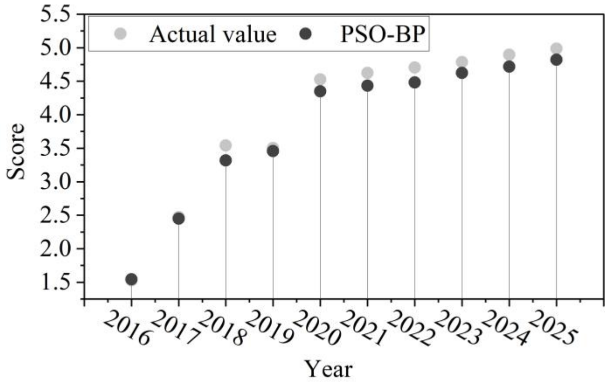

Figure 8. Teaching quality evaluation results

In order to verify the accuracy and validity of the information literacy teaching effect evaluation model based on PSO-BP,PSO-BP was compared with GA-BP,DA-BP and BP.Particle Swarm Algorithm Parameters:Maximum number of iterations T=100,Population size N=10,Learning factor c1=c2=2, Search Interval[-1,1]. Genetic Algorithm (GA) Algorithm Parameters: Population size N=10, Maximum number of iterations T=150, Crossover probability=0.6, Mutation probability=0.1. The parameters of the BP neural network are set as follows: the number of input nodes in the input layer is inputnum = 25, the number of hidden nodes is hiddennum = 50, and the number of output nodes is outputnum = 1. The maximum training times of the BP neural network is 2000. The transfer functions of the hidden layer and the output layer are logsig and purelin respectively. The training function is trainlm, the learning rate is 0.01, and the training error target is 0.001. The comparison results of different algorithms are shown in Figure 9 and Table 3.

From Figure 9 and Table 3, it can be seen that from the overall evaluation results of information literacy education and teaching in colleges and universities, the evaluation results of PSO-BP are better than those of GA-BP, DA-BP and BP, and the RMSE of PSO-BP is the smallest and the correlation coefficient R reaches to the maximum in both training and testing sets, which means that the correlation degree between the evaluation values of information literacy teaching and the actual values of information literacy teaching evaluation of PSO-BP model is the highest, and the prediction effect is the best. The evaluation accuracy of PSO-BP, GA-BP and DA-BP is better than BP, which is mainly due to the fact that the group intelligence algorithms PSO, GA and DA optimally select the parameters of the BP model and improve the evaluation accuracy of the BP model.

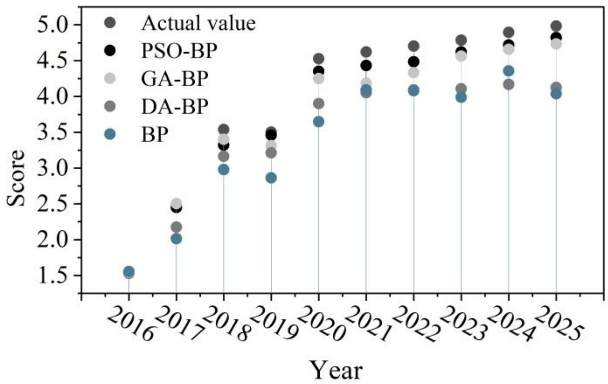

Figure 9. Evaluation of teaching quality of different algorithms

Table 3. Comparison of evaluation results from different algorithms

Method	**Training set**		**Test set**	
	RMSE	**R**	**RMSE**	**R**
PSO-BP	0.0091	0.995	0.0327	0.9884
GA-BP	0.0158	0.9777	0.0397	0.971
DA-BP	0.0154	0.9759	0.0456	0.9632
BP	0.0163	0.9661	0.048	0.9454

4.5. Application of Information Literacy Teaching Effectiveness Evaluation Models

The information literacy index data of colleges and universities were input into the PSO-BP evaluation model to get the information literacy index score of college students, and the results are shown in Table 4.

Information awareness, as the core of students' information literacy, is related to the upper limit of personal information literacy development. According to the scores of the indicators in the table, information awareness is the weakest in college students' information literacy, and compared with the other level 1 indicators of information awareness dimension, information awareness has the highest score of 2.49. However, the score of the level 2 indicator, recognizing the timeliness of information (B6), is significantly lower than that of recognizing the value and role of information (B5). Information neediness (A1) is particularly deficient, with a score of 2.25. The scores for the secondary indicators of being able to specify the information needed for one's own learning (B1) and being able to talk about the types and characteristics of the information one needs (B2) are only 2.27 and 2.23.

Information competence is the core element of information literacy, the stronger the information competence of college students, the higher the efficiency of applying innovation and absorbing and utilizing information, and vice versa, the lower it is. Information ability mainly includes information acquisition ability, information creation ability, information evaluation ability, information sharing ability and information management ability. According to the data in Table 4, it can be seen that although students' scores on the information competence dimension indicators are relatively high (2.74), there is still much room for improvement in the information-sharing ability (A12), especially in the ability to communicate and share information with the outside world through diversified information channels (B27).

Therefore, college students have strong information ability and a certain foundation of information literacy, but there is still room for improvement in information awareness and information application, and colleges and universities still need to pay attention to the systematic learning of students' information awareness and information application.

Table 4. Student information literacy evaluation index score

Dimension	Primary indicator	Mean value	Secondary indicator	Mean value
Information awareness(2.40)	A1	2.25	B1	2.27
			B2	2.23
	A2	2.46	B3	2.43
			B4	2.49
	A3	2.49	B5	2.55
			B6	2.42
Information application(2.46)	A4	2.41	B7	2.70
			B8	2.24
			B9	2.29
	A5	2.50	B10	2.35
			B11	2.65
Information ethics(2.44)	A6	2.38	B12	2.26
			B13	2.49
	A7	2.50	B14	2.44
			B15	2.41
			B16	2.64
	A8	2.44	B17	2.38
			B18	2.53
			B19	2.41
Information ability(2.74)	A9	2.89	B20	2.74
			B21	2.55
			B22	2.49
	A10	2.77	B23	2.64
			B24	2.30
	A11	2.68	B25	2.63
			B26	2.12
	A12	2.52	B27	2.05
			B28	2.39
	A13	2.82	B29	2.61
			B30	2.42

5. Conclusion

This study proposes an evaluation model based on improved PSO-BP neural network for the purpose of improving BP neural network to predict the teaching effect of information literacy education in colleges and universities. The evaluation index system of information literacy teaching is established in terms of information awareness, information application, information ethics and information competence. The experimental conclusions drawn in this paper are as follows:

(1) Through the experiment, it can be obtained that the improved BP neural network of PSO algorithm is more stable and faster to reach the ideal error precision than the connection weight learning process before the improvement, and its predicted output value is basically in line with the expected value. This proves that the improved BP neural network can effectively enhance the global optimization ability, reduce the convergence oscillation trend, improve the training speed of the algorithm, and obtain high accuracy evaluation results. The model is highly feasible and scientific for solving this kind of nonlinear relationship problem of teaching evaluation.

(2) Through the empirical application of the evaluation model of information literacy teaching effect, it is found that the information awareness of college students' information literacy has the highest score of 2.49, while the scores of being able to clarify the information needed for their own learning, and being able to talk about the types and characteristics of the information they need are only 2.27 and 2.23, which shows that college students are more capable of information, but there is still a need to strengthen and improve the information awareness and information application. However, in information awareness and information application, they still need to be strengthened and upgraded.

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