



Evaluation Method of Classroom Teaching Effect Under Intelligent Teaching Mode

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Accepted: 9 February 2022 / Published online: 9 March 2022

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Abstract

In order to improve the accuracy and performance of classroom teaching effect evaluation, an intelligent teaching mode classroom teaching effect evaluation method is proposed. Based on the characteristics of intelligent teaching mode, an intelligent teaching effect evaluation index system including five indexes of basic quality, teaching attitude, teaching method, teaching ability and teaching effect is constructed. After obtaining the scores of each index by expert scoring, it is input into the cuckoo search algorithm extreme learning machine evaluation model and solved by objective function, obtain the final score of teaching effect evaluation. The experimental results show that the proposed method can effectively improve the evaluation accuracy of classroom teaching effect of intelligent teaching mode, and provide a new method for classroom teaching effect evaluation.

Keywords Intelligent course · Teaching mode · Classroom teaching effect · Cuckoo algorithm · Extreme learning machine

1 Introduction

Different from traditional teaching methods, online teaching is not limited by time and place, which is more conducive to students' effective use of scattered spare time for independent learning to meet the learning needs of different students [1]. But online teaching also has some shortcomings: teachers and students' face to face communication is insufficient, lack of effective learning supervision mechanism. Therefore, at present, traditional teaching is still the main way of teaching in colleges and universities. It is also a direct and systematic way to impart knowledge under the condition of large classes. The disadvantages of traditional teaching are obvious: students' subjectivity is not taken seriously, the rhythm of classroom teaching is mastered by teachers, students passively accept knowledge, and they are not interested in the simple preaching mode, so the teaching effect is not ideal. Under the current background, colleges and universities should effectively integrate traditional

classroom teaching and online teaching, give full play to their advantages, maximize the teaching effect, and realize the teaching innovation of colleges and universities to carry out intelligent courses [2].

Since the reform and opening up, the reform of teaching mode in Colleges and universities across the country has been carried out continuously, integrating intelligent elements into the classroom, promoting teaching reform, giving full play to the leading role of education and improving teaching level [3]. Although the classroom teaching reform has made great achievements, the previous classroom teaching reform mainly focused on the teaching content and curriculum, while the reform of the evaluation system of its teaching effect seems to be quite lagging behind. The application of artificial intelligence technology provides a large amount of Knowledge Inventory for college students, which makes today's education model develop innovatively [4]. In the current environment, when analyzing the influence of intelligent teaching mode, attention should also be paid to analyzing the existing problems, and then carry out corresponding reforms [5, 6].

Taking the University of Catalonia as an example, Prat et al. evaluated all online teaching evaluations of the school during COVID-19, revealing teaching developments at all levels (holistic, central and disciplinary) [7]. The data obtained from the virtual platform provided extremely

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valuable information about what was being done in the classroom. Data obtained from Atenea, Moodle virtual platform of the University of Catalan Politics (UPC), during the COVID-19 pandemic were analysed and the results discussed. However, this method does not consider the special attributes of different courses, so the evaluation effect needs to be further improved. Cvetkovic et al. evaluated the role of ICT sector in the teaching process and the strategic cooperation between universities and industry [8]. The main purpose of this study was to evaluate ICT sector in the teaching process according to the attitude of teachers and the strategic collaboration between universities and industry. A survey of students and ICT teachers working in ICT was conducted to reveal the relationship between the skills required for the job and those of university professors; whether the employment skills of recent graduates increase the chances of employment. However, this method does not carry out in-depth analysis on the teaching quality of the professional courses, but evaluates the employment opportunities as the entry point. In order to improve the accuracy of college teaching quality evaluation, Li et al. proposed a college teaching quality evaluation method based on DA-BP [9]. The analytic hierarchy process is used to construct the college teaching quality evaluation index system. The evaluation index score is used as the input of DA-BP and the comprehensive score of College Teaching quality is used as the output of DA-BP. This method can evaluate the classroom teaching quality. However, the consideration is relatively single, and there is no in-depth comprehensive analysis and evaluation. Guo et al. proposed a statistical modeling for classroom teaching evaluation and a comprehensive model based on integrated learning by using artificial intelligence technologies such as computer vision and intelligent speech recognition [10]. This method can evaluate the quality of classroom teaching in colleges and universities, but its cost is too high, so it is not suitable for popularization and application. An et al. calculated the weights of different categories of features by using the ratios of the same attributes among multi-label data objects of features to complete the evaluation of the quality feature classification effect [11]. This method has high accuracy in evaluation and a relatively simple evaluation process, but it is limited to use after classification.

Although the above methods have realized classroom teaching effect evaluation or teaching quality evaluation from different angles and sides, they do not consider the special attributes of different courses, resulting in low evaluation accuracy and high cost investment. Therefore, this paper proposes a classroom teaching effect evaluation method under the intelligent teaching mode. Firstly, the method traverses and excavates the classroom teaching effect evaluation indexes through the cuckoo search algorithm. In order to avoid the problems of too many local minimum iterations and low accuracy of performance index

and learning rate, the extreme learning machine evaluation model is constructed. In order to obtain excellent classroom teaching effect evaluation performance and further improve the evaluation accuracy.

2 Evaluation model of intelligent teaching effect based on CS-ELM algorithm

The basic design idea of intelligent network course is an excellent teaching process, which must be able to intelligently select teaching strategies and dynamically adjust teaching micro strategies according to teaching objectives, teaching contents and students' specific conditions [12, 13]. In order to improve the management level of students under the intelligent education mode, we must guide and help based on the actual situation of students, formulate a teaching mode suitable for students' own development characteristics, continuously optimize and innovate strategies to increase the level of management students and gradually improve them, so as to realize their existing development significance and target value. Therefore, an intelligent teaching effect evaluation model based on CS-ELM algorithm is proposed. As the performance of extreme learning machine model is affected by the selection of initial input weight and hidden layer bias, the cuckoo search algorithm is applied to the selection of initial input weight and hidden layer bias of ELM model, and an intelligent teaching effect evaluation model based on CS-ELM algorithm is proposed.

2.1 Mining of teaching effect evaluation index based on cuckoo search algorithm

Cuckoo search algorithm is referred to as CS algorithm. The natural cuckoo finds a suitable nest site for laying eggs. The process is carried out in a random manner [14]. Three conditions are proposed to imitate the cuckoo's nest search activity:

- (1) The cuckoo lays one egg at a time and randomly puts it into the selected bird's nest.
- (2) Among many bird nests, the cuckoo keeps the best nest to the next generation [15].
- (3) The number of bird's nests available is n fixed, and the probability of the bird's nest owner detecting a bird's egg is $P_a \in [0, 1]$. Use formula (1) to describe the path and location of the cuckoo's nest search:

$$\chi_i^{(t+1)} = \chi_i^t + \alpha \oplus L(\lambda), i=1, 2, \dots, n \quad (1)$$

In the formula: χ_i^t represents the position of the i -th bird's nest of the t th generation, α represents the step

control quantity, $\oplus$ represents the point-to-point multiplication, $L(\lambda)$ represents the Levy random search method, and $L \sim u = t^{-\lambda}$, ($1 < \lambda \leq 3$). After the bird's nest location is updated, compare P_a with $r \in [0, 1]$. When $r \leq p_a$, $\chi_i^{(t+1)}$ remains unchanged, on the contrary, $\chi_i^{(t+1)}$ randomly changes; the bird's nest location $y_i^{(t+1)}$ that retains the optimal solution through the above method is still recorded as $\chi_i^{(t+1)}$.

The new solution generated by random preference swimming instead of the solution discarded by the bird's nest host is described by formula (2):

$$\chi_i^{(t+1)} = \chi_i^t + r(X_n^t - X_m^t) \quad (2)$$

In the formula: r represents the scaling factor between (0, 1); X_n^t, X_m^t represents the random position of the two bird's nests of the t generation.

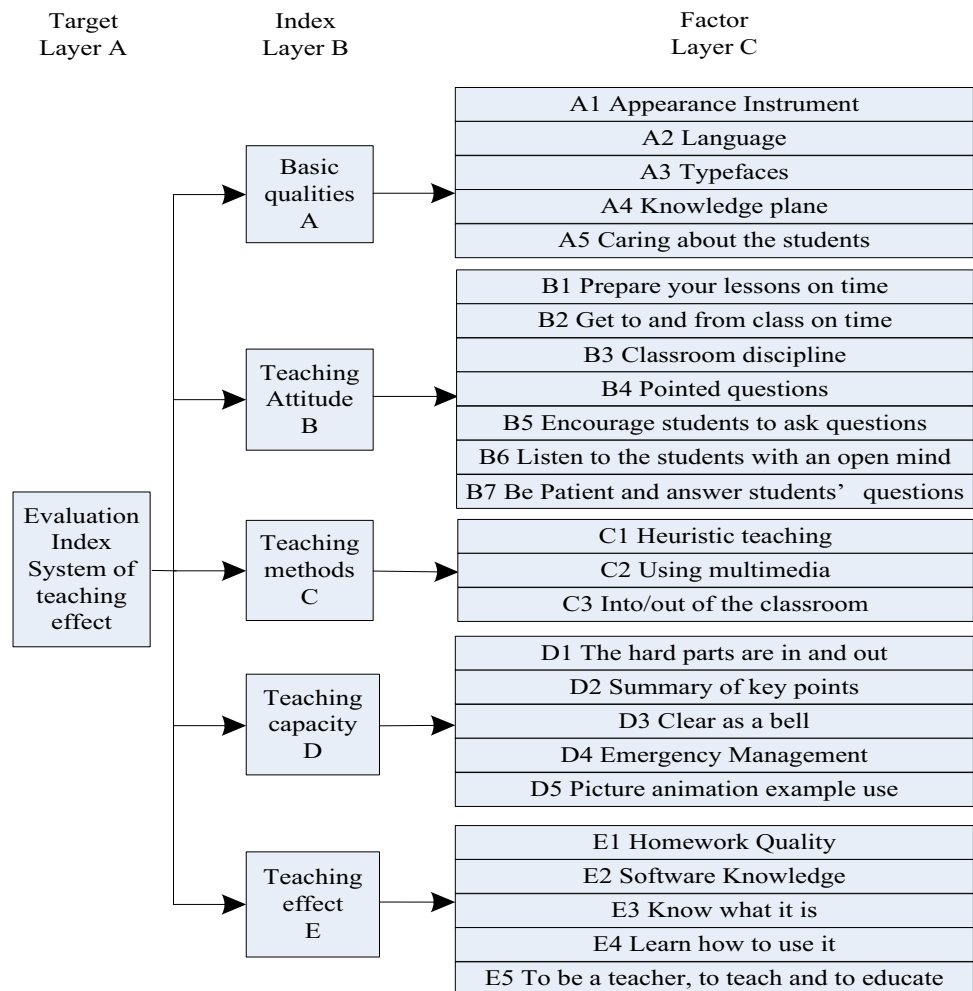
According to the cuckoo search algorithm, the teaching effect evaluation indexes in the process of intelligent course teaching are mined. In order to correctly and effectively evaluate the situation of intelligent teaching effect, follow the principles of scientific, systematic, concise, objective,

comprehensive, comparable and measurable selection of evaluation indexes [16], reflect the influence of each evaluation index to the greatest extent, and construct an intelligent teaching effect evaluation index system, which is described in Fig. 1. It mainly includes three levels: target level, criterion level and element level, including 5 primary evaluation indicators and 25 secondary evaluation indicators.

2.2 Objective function construction based on extreme learning machine

Based on the above index system, in order to further improve the accuracy of classroom teaching evaluation, Based on limit learning machine (extreme learning machine, ELM) constructs the objective function. Elm network has the advantages of simple structure and fast learning speed, and uses Moore Penrose generalized inverse to solve the network weight and obtain a smaller weight norm, which can avoid many problems caused by cuckoo search algorithm, such as too many local minimum iterations, determination of performance index and learning rate, and obtain good results

Fig. 1 Evaluation index system of teaching effect under intelligent teaching mode



Network generalization performance of [17]. The model structure is shown in Fig. 2.

A standard single hidden layer feedforward neural network containing N training sample $\{x_i, y_i\}, i = 1, \dots, N$ and

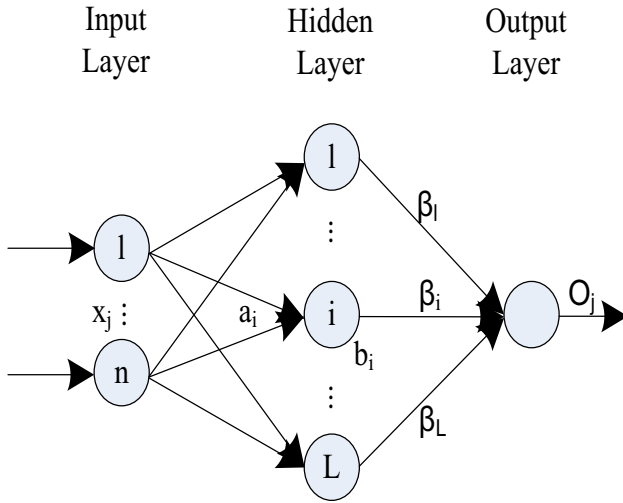


Fig. 2 ELM model structure diagram

$\tilde{N}$ hidden layer nodes for teaching effect index, and whose excitation function is $g(x)$, can be expressed as follows:

$$\sum_{i=1}^{\tilde{N}} \beta_i g w_i x_j + \sum_{i=1}^{\tilde{N}} \beta_i g b_i = o_j, j = 1, \dots, N \quad (3)$$

where, w_i represents the input weight of the input neuron and the i hidden layer node; β_i represents the output weight of the i hidden layer node and the output neuron. Table b_i shows the bias of the i hidden layer node; o_i represents the output value of the j input sample.

The standard single hidden layer feedforward neural network with N hidden layer nodes and excitation function $g(x)$ can approach N training sample $\{x_i, y_i\}$ with no error, namely:

$$\sum_{j=1}^{\tilde{N}} |o_j - y_j| = 0 \quad (4)$$

Therefore, there exist w_i, β_i and b_i that enable:

$$\sum_{i=1}^{\tilde{N}} \beta_i g w_i x_j + \sum_{i=1}^{\tilde{N}} \beta_i g w_i x_j b_i = y_j, j = 1, \dots, N \quad (5)$$

Equation (5) can be expressed as:

$$H\beta = Y \quad (6)$$

Type:

$$H(w_1, \dots, w_{\tilde{N}}, b_1, \dots, b_{\tilde{N}}, x_1, \dots, x_N) = \begin{bmatrix} g(w_1 x_1 + b_1) & \dots & g(w_{\tilde{N}} x_N + b_{\tilde{N}}) \\ \vdots & \dots & \vdots \\ g(w_1 x_N + b_1) & \dots & g(w_{\tilde{N}} x_N + b_{\tilde{N}}) \end{bmatrix}_{N \times \tilde{N}} \quad (7)$$

where, H represents the hidden layer output matrix of the neural network, and column i in H is the output vector of the i hidden layer node corresponding to the input sample $x_1, x_2, \dots, x_N$. Therefore, network parameters are constantly adjusted by solving the following minimization problem.

$$\min \|H\beta - Y\| \quad (8)$$

Traditional SLFNs needs to find a set of optimal parameters $\hat{w}_i, \hat{b}_i, \hat{\beta}$, ($i = 1, \dots, \tilde{N}$), so that:

$$\|H(\hat{w}_1, \dots, \hat{w}_{\tilde{N}}, \hat{b}_1, \dots, \hat{b}_{\tilde{N}})\hat{\beta} - Y\| = \min_{w_i, b_i, \beta} \|H(w_1, \dots, w_{\tilde{N}}, b_1, \dots, b_{\tilde{N}})\beta - Y\| \quad (9)$$

H is usually obtained by gradient-based learning. When the excitation function is infinitely differentiable, network parameters do not need to be adjusted completely. Input connection weights and hidden layer node bias can be randomly selected at the beginning of training, and their values can be fixed in the training process. The output connection weights can be obtained by solving the least square solution of the following linear equations:

$$\|H(\hat{w}_1, \dots, \hat{w}_{\tilde{N}}, \hat{b}_1, \dots, \hat{b}_{\tilde{N}})\hat{\beta} - Y\| = \min_{\beta} \|H(w_1, \dots, w_{\tilde{N}}, b_1, \dots, b_{\tilde{N}})\beta - Y\| \quad (10)$$

The least square solution of the linear equation is:

$$\hat{\beta} = H^+ Y \quad (11)$$

where H^+ represents the Moore–Penrose generalized inverse of the hidden layer output matrix H [18]. The optimal solution $\hat{\beta}$ has the following characteristics:

- (1) The minimum training error can be obtained through this solution;
- (2) Get the minimum normal form of weight vector and get the best generalization performance;
- (3) The least squares solution of normal form is unique, so the algorithm will not produce a local optimal solution.

ELM algorithm:

Given that the training sample $\{x_i, y_i\}, i = 1, \dots, N$ the number of hidden layer nodes is $\tilde{N}$, and the excitation function is $g(x)$, the standard single hidden layer feedforward neural network algorithm process is divided into three steps:

- (1) Set the input weight w_i and bias $b_i, i = 1, \dots, \tilde{N}$ immediately;
- (2) Compute the hidden layer output matrix H ;

Calculate the output weight $\beta: \hat{\beta} = H^+ Y$.

Therefore, compared with traditional SLFNs, ELM does not need to adjust the values of w and b during training, but only needs to adjust the value β according to the corresponding algorithm to obtain a global optimal solution. The process of parameter selection is relatively easy, the training speed is significantly improved, and it will not fall into local optimal [19].

Considering that the performance of ELM model is affected by the selection of initial input weight w_i and hidden layer bias b_i , the CS algorithm is applied to the selection of initial input weight w_i and hidden layer bias b_i of ELM model, and an evaluation objective function of teaching effect of intelligent courses based on CS-ELM is proposed:

$$\min F = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - o_i)^2} \quad (12)$$

where y_i and o_i represent expected output and actual output respectively; n represents the number of training set samples.

2.3 Algorithm process

Based on the above algorithm analysis, the CS algorithm is improved by using ELM model. By adjusting the number of hidden layer nodes of ELM, the optimal set of input weights and thresholds are selected, and compared with the best nest position generated by CS algorithm, so as to further improve the accuracy and stability of classroom teaching evaluation and reduce training time. The specific implementation process is as follows: firstly, the intelligent teaching effect evaluation index is constructed from the five aspects of basic quality, teaching attitude, teaching method, teaching ability and teaching effect [20], and then the score and final score of each evaluation index are obtained by expert scoring. Then, the score of each evaluation index is used as the input of CS-ELM and the final score is used as the output of CS-ELM. An intelligent teaching effect evaluation model of CS-ELM is established. Among them, the scores of each evaluation index and the comprehensive scores of intelligent teaching effect evaluation are obtained by the expert evaluation method. The scores of each evaluation index are 1, 0.7, 0.5, 0.3 and 0.1 respectively, and the corresponding grades are excellent, good, medium, poor and poor respectively.

Step1: According to the index system in Fig. 1, read the evaluation data of intelligent teaching effect, divide the data into training set and test set, and normalize it;
Step2: Set CS algorithm parameters: the number of nests is N , the maximum number of iterations is M , and the probability of foreign birds' eggs being discovered by the nest host is p_a . Calculate all nest objective function values according to Eq. (11).

Step3: Update the nest position according to Formula (1), calculate the objective function value of the nest after the update and compare it with the objective function value before the update, and take the nest with the better objective function value as the current position;

Step4: generate the random number $r, r \in (0, 1]$ for uniform analysis. If $r > p_a$, update the nest position according to formula (2), calculate all nest objective function values, and reserve the nest position with the best objective function value;

Step5: determine whether the algorithm terminates. If the termination condition is satisfied, the historical optimal solution is recorded. Otherwise, return to Step3;

Step6: The best bird's nest position corresponds to the best initial input weight w_i and the best hidden layer bias b_i of the ELM model, and the best initial input weight b_i and the best hidden layer bias w_i are substituted into the ELM model to evaluate the teaching effect of intelligent courses.

3 Data analysis and hypothesis verification

3.1 Algorithm effectiveness verification experiment

3.1.1 Data source

The data of this study are derived from the evaluation data of teaching effect of intelligent courses in a university from 2013 to 2021, and the maximum value method is adopted to standardize the obtained data. By comparing the teaching effect evaluation index data with the teaching effect evaluation score data, the score and final score of each evaluation index are shown in Tables 1 and 2.

3.1.2 Evaluation index

Root mean square error (RMSE) and correlation coefficient (R) are used as indicators to measure the evaluation performance of the effect of teaching in intelligent courses. Formula (13) and Formula (14) are described as follows:

$$RMSE = \sqrt{\frac{\sum_{k=1}^n (x_k - \text{pred}_k)^2}{n}} \quad (13)$$

$$R = \frac{1}{\sqrt{\sum_{k=1}^n x_k^2} \sqrt{\sum_{k=1}^n \text{pred}_k^2}} \sum_{k=1}^n x_k \text{pred}_k \quad (14)$$

where, n represents the number of samples; x_k and pred_k represent the actual and predicted scores of the k th sample.

Table 1 Evaluation index of intelligent education

Serial number	2013	2014	2015	2016	2017	2018	2019	2020	2021
1	0.0365	0.0431	0.0565	0.0685	0.0791	0.0719	0.0862	0.1351	0.2579
2	0.2259	0.1125	0.2516	0.2704	0.1598	0.1201	0.0683	0.1782	0.3223
3	0.2768	0.2865	0.2898	0.2942	0.2906	0.1876	0.0865	0.3541	0.3976
4	0.2732	0.2963	0.2864	0.2089	0.2154	0.1132	0.1364	0.1425	0.3712
5	0.3214	0.2457	0.0646	0.2993	0.1774	0.2443	0.1462	0.2512	0.3978
6	0.0597	0.1596	0.0534	0.0839	0.1504	0.0178	0.1241	0.1763	0.2906
7	0.0251	0.0482	0.0529	0.0664	0.0917	0.1186	0.1495	0.2138	0.3292
8	0.0448	0.0668	0.0512	0.0812	0.1809	0.0648	0.1244	0.2694	0.3116
9	0.0451	0.0621	0.0853	0.5941	0.0934	0.0668	0.0837	0.2954	0.3135
...	...	...	...	...	...	...	...	...	...
23	0.0512	0.0612	0.0711	0.0964	0.1772	0.0694	0.0696	0.1945	0.2564
24	0.0087	0.0858	0.0265	0.0349	0.1721	0.0579	0.0712	0.1891	0.3419
25	0.1054	0.1204	0.0435	0.0591	0.0537	0.0493	0.0629	0.1765	0.3395
26	0.0584	0.0235	0.0253	0.114	0.0467	0.0579	0.0515	0.1821	0.3846

Table 2 Total score of intelligent education evaluation

Year	2013	2014	2015	2016	2017	2018	2019	2020	2021
Score P	1.6263	1.6518	2.7269	3.9266	4.9957	5.1295	5.2587	5.5912	5.9542

Table 3 Ranking of evaluations

Corresponding score	Evaluation result
[5.2.6)	That's good
[4.5.5.2)	Better
[3.2.4.5)	Normal
[2.1.3.2)	Worse
[1.5.2.1)	Very bad

3.1.3 Results analysis

The teaching effect is divided into five grades: very good, good, general, poor and very poor. The grade of evaluation is shown in Table 3.

Nine sets of data were obtained from expert scoring during 2013–2021. The evaluation data from 2013 to 2017 were used as the training set, and the evaluation data from 2018

to 2021 were used as the test set. The training set data were used to establish the evaluation method of CS-ELM intelligent course teaching effect. The test set data is used to verify the correctness of the method. In order to highlight the advantages of CS-ELM intelligent course teaching effect evaluation method, CS-ELM and PSO-ELM, GA-ELM and ELM were compared. Parameter Settings are shown in Table 4.

The evaluation results of intelligent teaching effect are shown in Table 5 and Fig. 3.

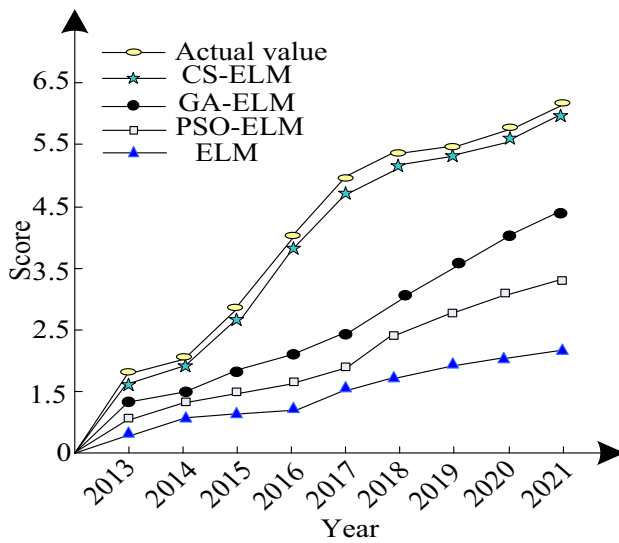
From the overall evaluation of intelligent teaching effect, the result of CS-ELM is the best, which is closer to the actual teaching effect evaluation result than 98%. Therefore, it can be seen that the effect of this method is the best; The evaluation accuracy of CS-ELM, GA-ELM and PSO-ELM is better than that of single elm, mainly because CS, GA and PSO algorithms optimize the weight and bias involved in elm model, which greatly improves the evaluation accuracy of intelligent teaching effect by using elm model.

Table 4 Algorithm parameter settings

Evaluation model	Parameter setting
ELM	Hidden layer neurons dennum = 40
GA-ELM	The population size of genetic algorithm (Ga) is 30, the maximum iteration number is 200, the crossover probability is 0.9, the mutation probability is PM=0.3
PSO-ELM	The population size of paper swarm optimization (PSO) is 20, the maximum iteration number is 200, learning factor C1=C2=3, inertia weight w=0.3
CS-ELM	Population size M=10, maximum number of iterations t=100, discovery probability PA=0.36, optimal range of variables [-1,1]

Table 5 Comparison of teaching effect evaluation results under intelligent teaching mode

Method	Training set RMSE	Training set R	Test set RMSE	Test set R
ELM	0.029	0.885	0.067	0.933
CS-ELM	0.021	0.867	0.048	0.878
PSO-ELM	0.028	0.866	0.058	0.856
GA-ELM	0.031	0.862	0.041	0.861

**Fig. 3** Evaluation results of teaching effect

3.2 Evaluation performance analysis

3.2.1 Setting of performance evaluation experiment

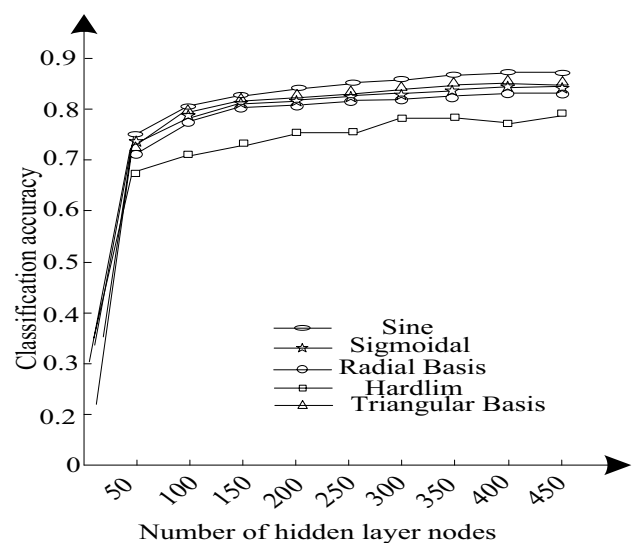
The data of 10 classes in the school were selected as experimental data, of which 6 classes were used as Train sets, with a total sample number of 3150. The data of two of the remaining four classes were used as Validation sets with 421 samples to determine the optimal parameters of the model. The data of the last two classes were used as Test sets, with 431 samples.

Through the divided training set and test set, this paper determines the optimal parameter comparison results of reference [9] university teaching quality evaluation method based on da-bp algorithm, reference [10] establishing classroom teaching evaluation model dominated by artificial intelligence application based on statistical model and integrated learning. The Gaussian kernel function was selected as the kernel function, and the kernel parameter $\gamma = \frac{1}{2}Q^2$ and the classifier penalty parameter C were selected by the tenfold cross verification method. Finally, the optimal training parameter was $C = 128$, $\gamma = 8$, and the maximum

recognition accuracy of the verification set was 86.5%. The cross-validation process took 40 min.

Extreme learning machine only needs to select the number of hidden layer nodes in the case of determining the excitation function, the process of parameter determination is relatively simple. Therefore, different incentive functions (Sine function, Sigmoidal function, Radial Basis function, Hardlim function and stationarity Basis function) are selected respectively. Meanwhile, the number of hidden layer nodes of each incentive function is initialized to 10, and the number of hidden layer nodes is increased with a cycle of 20. The influence of ELM with different excitation function and hidden node number on teaching effect evaluation accuracy was analyzed. See Fig. 4 for the analysis results of parameter selection. The parameter selection process takes 3 min.

It can be seen from the analysis in Fig. 4 that in the evaluation of teaching effect, the classification error result of Hardlim incentive function is the largest compared with other incentive functions, and the test accuracy of the other four incentive functions is similar. Among them, Sine incentive function has the highest accuracy in classifying the verification set, reaching 88.02%. When the number of hidden layer nodes of the five incentive functions exceeds 50, the corresponding classification accuracy begins to stabilize. When the number of hidden layer nodes is about 400, the classification accuracy reaches the highest and does not rise. Therefore, the classification accuracy of the method in this paper will increase monotonically with the increase of the number of hidden layer nodes, and will tend to be stable when the accuracy reaches a certain degree. It will not inhibit the classification accuracy after the number of hidden layer nodes of BP network reaches a certain scale.

**Fig. 4** Test error corresponding to different excitation functions

Based on the above analysis results, Sine excitation function is selected as the excitation function in this paper.

3.2.2 Analysis of performance evaluation results

According to the above experimental settings, three methods are used to train the training set according to the optimal parameters selected, and the CPU Time of the three methods is recorded during the training. After the training, the sample data of the remaining two classes were used for testing, and the evaluation accuracy of the three methods was compared. The comparison results of the performance parameters of the three methods are shown in Table 6.

As can be seen from Table 6, by comparing with the identification results of reference [9] and reference [10], it can be seen that the identification result of this method is the best. In terms of learning speed, the time consumed by this method is significantly less than that of reference [9] and reference [10]. The training time of this method is 3.4 s, and this method can achieve the same as that of reference [9] and reference [10] only by using fewer hidden layer nodes reference [10] has quite good prediction effect, and the prediction accuracy reaches 88.02%. Therefore, the identification effect of this method is good, the evaluation accuracy of teaching effect is very high, the division accuracy is improved, which proves its effectiveness in teaching effect evaluation, and the overall performance of this method is excellent.

4 Discussion

Under the network intelligent environment, the classroom teaching reform under the intelligent teaching mode is facing many opportunities and challenges. Network intelligent environment is conducive to the cross transformation of subject and object identity and the diversification of communication forms, the diversification of curriculum content and the flexibility of educational methods, as well as the diversity and universality of curriculum management resource development. At the same time, under the network intelligent environment, the curriculum teaching reform also faces many challenges. In the network intelligent environment, the cross transformation and interaction between

subject and object of curriculum restrict the determination of communication entities, the diversification of curriculum content and the flexibility of methods restrict the exertion of the dominance of authority and mainstream ideas, and the diversity and universality of curriculum resources restrict the unified implementation of management.

Intelligent teaching mode can guide students to form correct values. Employment value orientation is the core factor of employment outlook and the embodiment of world outlook, outlook on life and values in the process of employment. The students' employment values cultivated under this mode have more obvious social orientation, hope to contribute to the development of social productivity through their own professional knowledge, and have a higher awareness of serving the society. It can be seen that the employment orientation of College Students under the intelligent teaching mode is still higher than the social orientation.

5 Conclusion

This study proposes a cs-elm model for the evaluation of intelligent teaching effect. The results show that compared with ga-elm, pso-elm and elm, this method can effectively improve the accuracy of intelligent teaching effect evaluation, and provides a new method for intelligent teaching effect evaluation; However, there are few factors that can be studied at present, and more influencing factors will be studied in the future to improve the adaptability of the model; In addition, for the randomization of the initial weight and hidden layer bias of the elm model, the nuclear limit learning machine is introduced into the intelligent teaching effect evaluation to improve the stability of the model. This method basically realizes the overall evaluation, realizes the presentation of individual situation effect, and corrects the deviation in the process of education, which can improve the evaluation of teaching effect. By making full use of technical means to collect and integrate students' learning process data and learning result data, and integrating expert evaluation to classify the data, we can make a multidimensional, comprehensive, in-depth and reliable evaluation on the teaching effect of intelligent teaching mode.

By effectively combining CS algorithm and elm, this paper constructs the classroom teaching effect evaluation model of intelligent teaching mode, and more accurately evaluates the classroom teaching effect of this mode by selecting scientific, systematic, concise, objective, comprehensive, comparable and measurable evaluation indicators, so as to cultivate the ability of quality education Honesty education permeates into professional courses and various practical teaching. In the future, we should continue to strengthen and deeply implement curriculum education, promote students' learning and experience, effectively promote

Table 6 Comparison of performance parameters between two algorithms

Method	Training time/s	Neurons number	Test classification accuracy/%
Text methods	3.4	450	88.02
Reference [9]	6.34	1566	77.38
Reference [10]	9.69	1868	69.57

whole process education, collaborative education and all-round education, comprehensively improve students' comprehensive quality, and help further implement the “healthy China” strategy.

Acknowledgements This paper was funded by Educational reform fund project of Zhengzhou SIAS University with No. 2021jgzd07, and Industry-University Cooperative Education Program of the Ministry of Education of China with No.202101062044).

Declarations

The authors have no relevant financial or non-financial interests to disclose. Jing Chen provided the algorithm and experimental results, wrote the manuscript, Hui Lu revised the paper, supervised and analyzed the experiment. We also declare that data availability and ethics approval is not applicable in this paper.

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