Application Deep Extreme Learning Machine in Multi-dimensional Smart Teaching Quality Evaluation System

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Abstract

INTRODUCTION: The construction of the wisdom teaching evaluation system, as the essential part of the institution's teaching reform, is conducive to developing the institution's disciplines, making the existing teaching more standardized, and making the means of teaching diversified, intelligent, and convenient.

OBJECTIVES: Aiming at the current intelligent teaching evaluation design method, there are evaluation indexes that need to be more comprehensive, a single method, and system standard limitations.

METHODS: Proposes an intelligent optimization algorithm for a multi-dimensional innovative teaching quality evaluation method. First of all, the multi-dimensional wisdom teaching evaluation system is constructed by analyzing the influencing factors of teaching quality evaluation; then, the parameters of the depth limit learning machine are optimized by the bird foraging search algorithm, and the multi-dimensional wisdom teaching evaluation model is constructed; finally, the validity and stability of the proposed method are verified by the analysis of simulation experiments.

RESULTS: The results show that the proposed method improves the accuracy of the evaluation model.

CONCLUSION: Solves the problem of low evaluation accuracy and incomplete system of teaching quality evaluation methods.

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1. Introduction

With the development of artificial intelligence, big data, machine learning, and other technologies, profound changes have occurred in education and the informatization and intelligent transformation and upgrading of education. Brilliant teaching is the development and derivation of intellectual education, using advanced technologies such as artificial intelligence, big data, the Internet, virtual reality, and other advanced technologies to build an intelligent education platform, which promotes scholars to learn more deeply, expand their horizons, and develop themselves, and realizes the intelligence of teaching [1].

The construction of the intelligent teaching evaluation system, as an essential part of the institution's teaching reform, is conducive to developing the institution's disciplines, making the existing teaching more standardized, and making the teaching means diversified, intelligent, and convenient. Therefore, studying intelligent teaching evaluation systems is an urgent and essential research topic [2].

As a vital part of the intelligent teaching evaluation system, the innovative teaching quality evaluation method is related to the quality of teachers' teaching, students' post-course feedback, and the judgment standards of experts in the teaching field [3]. The innovative teaching quality evaluation method based on big data technology is a hot research topic. Literature [4] carries out educational evaluation measurement and data analysis from the

perspective of learning objectives and other perspectives and constructs a learning analysis model based on multilevel. Literature [5] utilized the pre-conceptual theory to determine the learning status accurately and gave the corresponding recommended learning resources. Literature [6] proposed a teaching-learning effect evaluation method based on learning motivation while using intelligent algorithms to define an intelligent teaching environment. Literature [7] proposed a method for constructing an innovative teaching motivation model by analyzing the perspectives of the professional field, cognitive judgment, and learners. Literature [8] suggested four innovative teaching cultivation models, including environment construction, creative behavior, cognitive learning, and learning assessment based on the artificial intelligence environment model. Literature [9] proposed a method based on intelligent teaching evaluation from four levels: data collection, storage, analysis, and learning. Literature [10] proposed an intelligent teaching evaluation model based on the experience model. Currently, teaching quality evaluation methods in universities include the questionnaire survey method [11], fuzzy comprehensive evaluation method [12], expert scoring method [13], support vector machine [14], neural network algorithm [15], and deep learning method [16]. The existing methods have the following shortcomings: 1) the evaluation indexes of intelligent teaching quality are not comprehensive enough and deviate from the teaching training objectives; 2) the evaluation indexes are limited to the final examination results and do not focus on other aspects of teaching; 3) the evaluation method of intelligent teaching quality is single, which does not guarantee the scientificity and plurality of the evaluation method; 4) the teacher, as the only evaluator, makes the standard of the existing evaluation system limited.

Extreme learning machine (ELM) is a single hidden layer structure, which leads to a reduction in the learning ability of ELM and a decrease in the prediction fitting accuracy when the dimensionality of the input data is too large. A deep extreme learning machine (DELM) [17] is a deep neural network stacked by multiple extreme learning machine self-encoders with fast training speed and good generalization performance. The simplicity of the structure of the Deep Extreme Learning Machine and the good evaluation effect makes the research of an intelligent teaching quality assessment model based on the Deep Extreme Learning Machine algorithm become the hot spot of domain expert learning research.

Aiming at the problems existing in the current intelligent teaching evaluation design method, this paper proposes a multi-dimensional innovative teaching evaluation method based on the depth limit learning machine and intelligent optimization algorithm. The main contributions of this paper are (1) analyzing the influencing factors of teaching quality assessment, (2) constructing a multi-dimensional intelligent teaching quality assessment system, (3) optimizing the depth limit learning machine using the birds foraging search algorithm, and the same time proposing a dimensional intelligent teaching evaluation method based on the birds foraging search algorithm to optimize the depth limit learning machine; and (4) verifying the method of this paper through simulation to have a higher degree of evaluation accuracy.

2. Multi-dimensional intelligent teaching quality assessment system

To construct a multi-dimensional wisdom teaching quality assessment system, this paper analyzes the factors affecting the assessment of teaching quality. It makes an assessment index system from four elements: cognitive thinking, emotional communication between teachers and students, achievement of teaching goals, and teaching organization.

2.1 Analysis of factors affecting the assessment of teaching quality

In this paper, based on the third-generation teaching activity theory, the author analyzes the influence factors of teaching quality assessment from the dimensions of four elements: cognitive thinking, teacher-student emotional communication, achievement of teaching goals, and teaching organization [18], as shown in Figure 1.
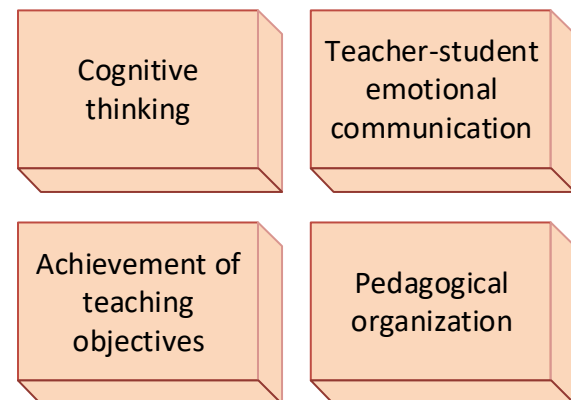

Figure 1 Multi-dimensional influences

The cognitive thinking dimension refers to the teacher stimulating students' thinking and positive feedback during intelligent teaching and learning. The cognitive thinking dimension mainly includes student thinking stimulation and evaluation feedback.

The teacher-student affective communication dimension refers to the mode style of the teacher's lecture and the student's learning experience after enjoying it in intelligent teaching. The teacher-student affective communication dimension mainly includes student learning experience and wise classroom art.

The dimension of teaching goal achievement refers to the reflection and achievement of teaching goals in intelligent teaching. Teaching goal achievement mainly includes teaching goal achievement and goal orientation.

The dimension of instructional organization and regulation refers to the control of instructional implementation and the process of student progress and

growth in intelligent teaching. The size of teaching organization and law mainly includes the overall development of students and the rule of an intelligent classroom.

2.2 Multi-dimensional Smart Teaching Assessment Indicators

The multi-dimensional bright teaching evaluation indicators are categorized in terms of eight influencing factors [19], which should include the following:

(1) Indicators of student thinking stimulation

Student thinking stimulation was assessed using indicators such as the number of times the teacher encouraged, teaching clarity of thinking, and conducting positive response questions to determine the extent to which the teacher stimulated students' divergent thinking.

(2) Evaluation feedback indicators

Evaluation feedback is positive feedback from teachers to students, as indicated by the number of teacher-initiated statements and student assessments.

(3) Indicators of student learning experience

Evaluative feedback indicates the degree of student participation in the learning experience during intelligent teaching and learning through the number of student-initiated presentations and student expression indicators.

(4) Smart Classroom Arts Indicators

Bright classroom art utilizes teachers' emotional expression, language frequency, communication frequency, and speed of speech to express the language art and emotion of brilliant classroom teachers.

(5) Indicators of achievement of teaching objectives

The accomplishment of teaching objectives is generally expressed in indicators such as students' monthly test scores, midterm and final grades, and the status of responding to knowledge points.

(6) Targeting indicators

Targeting is generally quantified in terms of the extent of knowledge points covered by innovative teaching, the amount of information, and the radiating surface of the knowledge map.

(7) Indicators of overall student development

Overall student development was quantified utilizing the length of time students spoke in the smart classroom, the length of time they studied outside of class, and the level of motivation expressed.

(8) Smart Classroom Regulation Indicators

Intelligent classroom moderation was quantified using classroom teacher question rate, response rate, guidance rate, and steady-state ratio.

2.3 Multi-dimensional wisdom teaching evaluation system construction

The multi-dimensional wisdom teaching assessment system takes cognitive thinking, teacher-student emotional communication, achievement of teaching goals

and teaching organization as the key elements [20], denoting the first-level indicators, and the eight influencing factors as the second-level indicators [21], and takes the number of times of encouragement by teachers, clarity of thinking in teaching, positive answers to questions in education, number of times of teacher-initiated speeches, number of times of assessment of students, number of times of student-initiated addresses, students' expression, teachers' emotional expression, language frequency, communication frequency, teaching speed, students' monthly test scores, midterm and final scores, responding to the knowledge point situation, the degree of knowledge point coverage, the amount of information, the radiation surface of the knowledge map, the length of students' speeches, the size of learning under the classroom, the degree of brain stimulation, the use of classroom teachers to ask questions, the response rate, the guiding rate, and the proportion of steady state as a tertiary indicator [22], and the specific schematic diagram of the assessment system is shown in Figure 2 Shown.
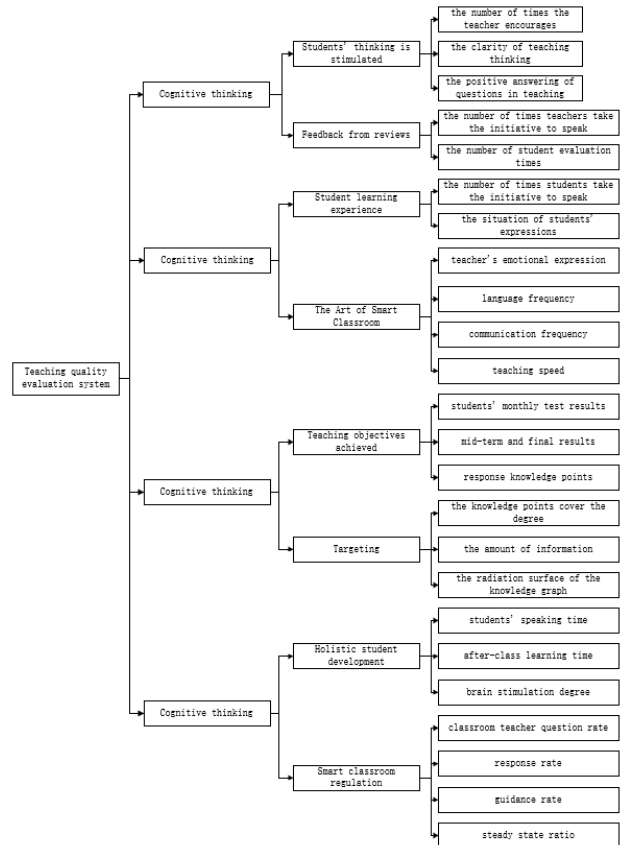

Figure 2 Teaching quality evaluation index system

3. Deep Extreme Learning Machine Network

The Extreme Learning Machine is a single hidden layer feedforward neural network whose most significant advantage is its fast learning rate. For a l remote layer node, the ELM can be expressed as

$$f_{ELM}(x_i) = \sum_{j=1}^{l} \beta_j g\left(a_j x_i + b_j\right), i = 1,2,\cdots,N \quad (1)$$

Where $\beta_j = \left[\beta_{j1}, \beta_{j2}, \cdots, \beta_{jn}\right]$ denotes the output weight of the j hidden layer unit, $a_j = \left[a_{j1}, a_{j2}, \cdots, a_{jm}\right]$ the input weight of the j hidden layer unit, the covert layer unit's bias, the j hidden layer unit, and the activation function of the undercover layer unit.

The ELM output error is

$$E = \sum_{i=1}^{N} \left\| f_{ELM}(x_i) - y_i \right\|$$
$$= \left\| H(a,b) \cdot \beta - y \right\| \quad (2)$$

Where H denotes the output of the hidden layer unit, the output weight, and the desired result. In the ELM algorithm, by determining a and b is uniquely determined. The equation solves the output weights

$$\beta^* = H^{-1} \cdot y \quad (3)$$

where H^{-1} denotes the Moore-Penrose generalized inverse matrix of the matrix H.

The output weights of the deep limiting learning machine consisting of multiple limiting learning machine self-encoders are

$$\beta^* = H^{-1} \left(\frac{1}{C} + HH^T \right)^{-1} \cdot y \quad (4)$$

where C represents the regular term coefficients. To reduce the complexity of training, two hidden layers are chosen in this paper, and the number of remote layer units in each layer is learned from the parameter experiments later.

4. Bird Foraging Search Algorithm

The overall framework of the Birds Foraging Search (BFS) [23] algorithm can be divided into three phases: the flight search behavior phase, the domain behavior phase, and the cognitive behavior phase. Among them, the flight search behavior and domain behavior phases can balance the exploration and exploitation capabilities of the algorithm, and the cognitive behavior phase can improve the overall search efficiency of the algorithm.

The central idea of the BFS algorithm is to use individuals to find the optimal food source. The location of the optimal food source corresponds to the global optimal solution, and the area of each bird corresponds to the site of a food source, i.e., a feasible solution to the optimization problem. The amount of food provided by the food source (the value of the fitness function)

indicates the quality of the solution. The number of birds is equal to the number of feasible solutions. Like other optimization algorithms, initialization must be completed before the algorithm is executed. The initial position of the birds in space is represented as follows:

$$X_i = UB - r_1 \cdot (UB - LB) \quad (5)$$

r_1 is a random value within the range of $[0,1]$.

In addition, the BFS algorithm has four ideal rules as follows:

1) The bird in the algorithm does not refer specifically to a particular type of bird but rather to an artificial bird that combines the behavior of all birds.

2) All birds live in flocks.

3) Only the currently optimal individual can occupy the territory.

4) The territory is considered a spatial prime, whose position is the same as the position of the current optimal individual.

(1) Flight search behavior phase

Raptors, such as falcons, often select an area with high prey potential and hover over it in search of prey. After intensive research, researchers have determined that the raptors' flight path resembles a logarithmic spiral [24]. The following logarithmic spiral equation can be used to describe this flight path:

$$X_i^{iter+1} = D_{i-p} \cdot e^{\theta} \cdot \cos(2\pi\theta) + PA^{iter} \quad (6)$$

Where $i \in [1,2,3,\ldots,N]$, and N denotes the population size. It is a random number in the range of $[-1,1]$ $D_{i-p} = \left| X_i^{iter} - PA^{iter} \right|$. Denotes the distance from the i th bird to the potential region, where X_i^{iter} denotes the position of the i th bird at the $iter$ th iteration, PA^{iter} is the position of the possible area at the $iter$ th iteration, and represents the current global optimum X_{best}^{iter}. In this stage, if an individual's new location has a better fitness value, it replaces its old location. As shown in Figure 3, the value of θ can be used to determine how close or far the next position of each bird in the population is from the potential region (most relative to the likely part when $\theta = -1$ and farthest from the possible area when $\theta = 1$ the logarithmic spiral flight pattern has a solid global search capability, and at the same time, ensures that the algorithm can be developed.
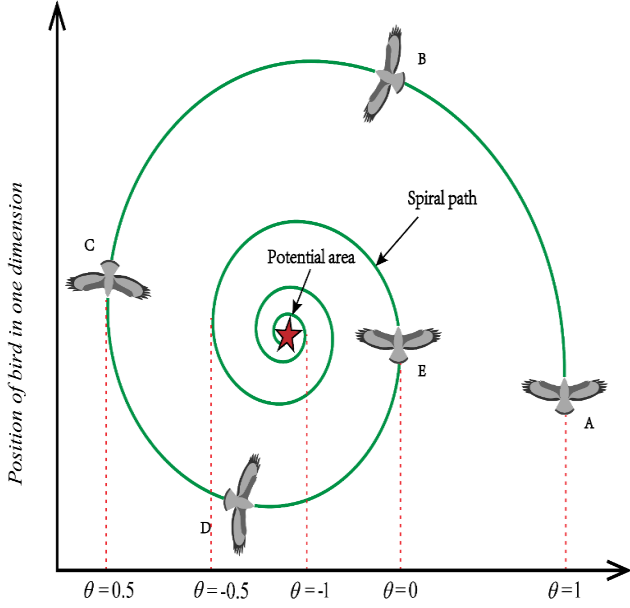
Figure 3 Logarithmic spiral flight pattern

(2) Stages of domain behavior

At this stage, the currently optimal individual is called a territorial bird, while the other individuals are called invasive birds. In BFS, different movement patterns exist between these two bird species. The territorial bird patrols a small area around its domain in search of better food sources on the one hand and protects its territory from other conspecifics on the other. This behavior can be expressed as:

$$X^{T,iter+1} = X^{T,iter} + r_d \cdot \lambda \qquad (7)$$

where $X^{T,iter}$ is the position of the territorial bird at the $iter$ th iteration of. It r_d is a random number with values in the range $[-1,1]$ that represents the search direction of the territorial bird. The scale factor allows the territory bird to make small movements at its current position. It is set to $(X^{T,iter} - X^{S,iter})$ where $X^{S,iter}$ is the suboptimal individual function.

All invading birds will move towards that territory after a territorial bird has taken over an area and become its exclusive domain. At this point, the territorial bird will protect its environment by chirping to repel the invaders. This process consists of two scenarios:

Scenario 1: The invasive bird is unaffected by the warning of the territorial bird and moves quickly towards the territory. Its position is updated below:

$$X_j^{I,iter+1} = X_j^{I,iter} + r_2 \cdot (X^{T,iter} - IF \cdot X_j^{I,iter}) \qquad (8)$$

Where $X_j^{I,iter}$ is the position of the j invasive bird at the $iter$ th iteration and r_2 is a random number with values in the range of $[0,1]$. IF known as the invasion factor, it determines how the position of the invasive bird changes. Figure 4.2 provides a vector representation of the invasive bird position update for different values IF. Figure 4

shows when $IF=1$ individuals perform localized searches ($X_j^{I,iter+1}$ between $X_j^{I,iter}$ and $X^{T,iter}$), whereas when $IF=2$ individuals focus on global searches ($X_j^{I,iter+1}$ in addition to $X_j^{I,iter}$ and $X^{T,iter}$). Therefore, to balance exploration and exploitation capabilities, the value of this parameter was set with equal probability to 1 or 2, i.e., $IF = round[1 + rand(0,1)\{2-1\}]$
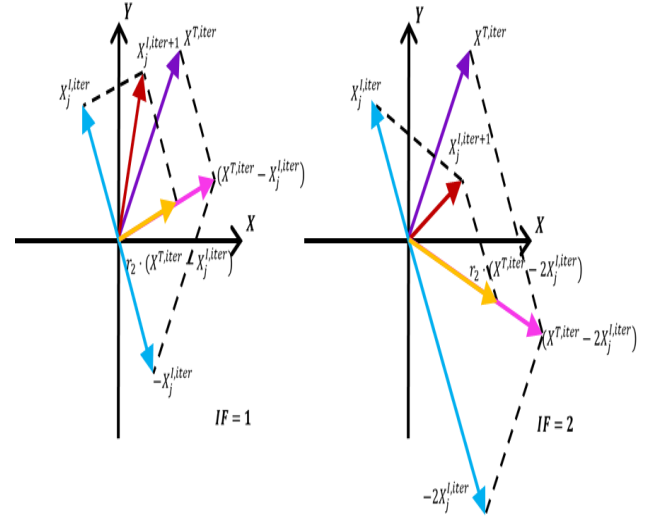

Figure 4 Vector representation of invasive bird movements with different invasion factors

Scenario 2: The warning of the territorial bird acts as a deterrent. The intruding bird j is startled and disperses in random directions, a process described by the following equation:

$$X_{j,d}^{I,iter+1} = X_{j,d}^{I,iter} + r_3 \cdot (X_{k,d}^{I,iter} - X_{m,d}^{I,iter}) + r_4 \cdot (X_{l,d}^{I,iter} - X_{h,d}^{I,iter})$$
$$(9)$$

where $j,k,m,l,h \in \{1,2,3,\cdots,N-1\}$ $j \neq k \neq m \neq l \neq h$ $d \in \{1,2,3,\cdots,D\}$ D denotes the dimensions of the problem. Moreover, there are random numbers with values in the range $[0,1]$.

In summary, the process for scenarios 1 and 2 can be summarized as follows:

$$\begin{cases} X_j^{I,iter+1} = X_j^{I,iter} + r_2 \cdot (X^{T,iter} - IF \cdot X_j^{I,iter}) & if\ P^{iter} \leq rand \\ X_{j,d}^{I,iter+1} = X_{j,d}^{I,iter} + r_3 \cdot (X_{k,d}^{I,iter} - X_{m,d}^{I,iter}) + r_4 \cdot (X_{l,d}^{I,iter} - X_{h,d}^{I,iter}) & otherwise \end{cases} \qquad (10)$$

Where P^{iter} denotes the probability that the territorial bird's warning worked and $rand$ is a random number with a value in the range $[0,1]$. Over time, the invading bird will gradually realize the bluff of the territorial bird. At the same time, the territorial bird's stamina will decline. Therefore, the warning of the territorial bird will gradually become ineffective for the invading bird. Consequently, P^{iter} can be described as follows:

$$P^{iter} = 1 - \frac{iter}{Max\text{-}iter} \qquad (11)$$

where P^{iter} decreases linearly from 1 to 0 with the number of iterations. From the optimization point of view, P^{iter} enables the algorithm to perform a global search with a significant probability at the beginning, then gradually shrink the search space and emphasize local search later. Thus, P^{iter} balances the algorithm's exploration and exploitation capabilities. Finally, the invasive bird is updated only if the fitness value of the new location is better; otherwise, its location will remain unchanged.

In addition, a role-switching mechanism has been incorporated throughout the search process. If an invasive bird discovers a better area than the other invasive birds and the current territorial bird, that invasive bird will become the new territorial bird in the following search round. In contrast, the original territorial bird will join the pushy bird team. This role-switching mechanism helps the algorithm avoid falling into local optimality.

(3) Cognitive-behavioral stage

Cognitive behavior is a process of self-learning that relies on accumulated experience: birds can use previous search information as their own experience to avoid unnecessary searches and thus improve foraging efficiency. To realize this process, the current and last retained location information are compared, and the comparison result is used as its experience for the next search. The whole cognitive behavior can be divided into two parts:

Scenario 1: The bird keeps finding better food sources, i.e., the current position differs from the previous one ($X_i^{iter} \neq X_i^{iter-1}$). This scenario indicates that the original search direction is correct, implying that it will likely search for a better food source if it continues in that direction. Therefore, in this phase, the individual will follow the original gradient information to learn. This targeted search can speed up the convergence of the algorithm. The following equation describes this process:

$$X_i^{iter+1} = X_i^{iter} + r_5 \cdot (X_i^{iter} - X_i^{iter-1}) \qquad (12)$$

where X_i^{iter} and X_i^{iter-1} denote the bird's position i in the $iter$ th iteration and $iter\text{-}1$ th iteration, respectively. r_5 is a random number in the range of $[0,1]$.

Scenario 2: The bird continues to search but needs help finding better results. That is, the current position is the same as the previous position ($X_i^{iter} = X_i^{iter-1}$). At this point, the bird realizes that its previous experience was incorrect, the original search direction is no longer applicable (the algorithm may fall into a local optimum), and it needs to change randomly. The process is implemented based on a Gaussian distribution:

$$X_i^{iter+1} = Gaussian(X_{best}^{iter}, \xi) \qquad (13)$$

Equation (13) aims to enable birds to find feasible locations within the region determined by the best individual. Is the optimal solution in the population in the $iter$ th iteration, and the expression ξ is as follows:

$$\xi = (\log(iter)/iter) \cdot abs(X_{best}^{iter} - r_6 \cdot X_i^{iter}) \qquad (14)$$

In the equation, r_6 is a random value within the range of $[0,1]$, used to enhance the distribution of new individuals when X_{best}^{iter} equal to X_i^{iter} $\log(iter)/iter$; it is used to adjust the size of the standard deviation. $\log(iter)/iter$ value decreases with the number of iterations, and the standard deviation decreases accordingly. Overall, this process makes the stochastic distribution of the global optimal solution more concentrated and produces a slight perturbation near the global optimal solution, improving the local search capability. Again, this process was retained only if the individual fitness values were better than the previous ones.

In addition, some individuals may search outside the boundary. To prevent such ineffective searches, BFS introduced a boundary control policy:

$$X_{i,d}^{iter} = UB - r_7 \cdot (UB - LB) \quad if \ X_{i,d}^{iter} < LB \ or \ X_{i,d}^{iter} > UB \qquad (15)$$

Where $X_{i,d}^{iter}$ is the position of the $d\text{-}th$ dimension of the i th individual at the $iter\text{-}th$ th iteration and r_6 is a random value in the range of $[0,1]$.

4. Optimization of Deep Extreme Learning Machine based on Bird Foraging Search Algorithm Method Ideas

(1) Coding method

This paper uses the actual number coding method to encode the hidden layer parameters. The specific coding method is shown in Figure 5. Figure 5 shows that the coding region is mainly divided into the secret layer weight values and the hidden layer bias l , the coding dimensions of the two hidden layer units m ' dimensional inputs $m \times l + l$, and the two hidden layers are $(m_1 \times l_1 + l_1) + (m_2 \times l_2 + l_2)$.

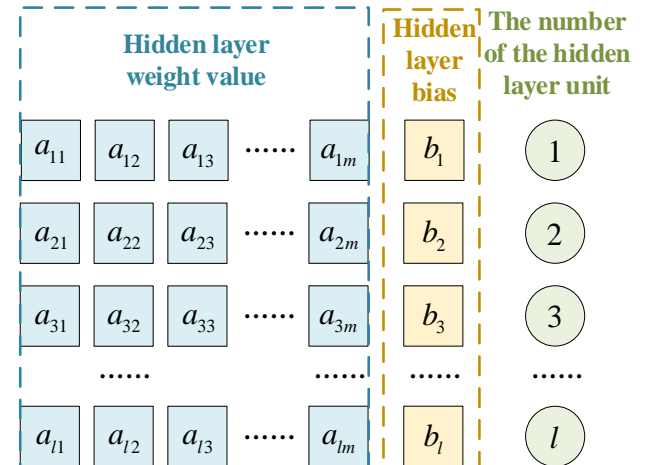| Hidden layer weight value					Hidden layer bias	The number of the hidden layer unit
a_{11}	a_{12}	a_{13}	......	a_{1m}	b_1	1
a_{21}	a_{22}	a_{23}	......	a_{2m}	b_2	2
a_{31}	a_{32}	a_{33}	......	a_{3m}	b_3	3
......					......	......
a_{l1}	a_{l2}	a_{l3}	......	a_{lm}	b_l	l

Figure 5 How DELM parameters are encoded

(2) Adaptation function

To accurately reflect the training DELM network strengths and weaknesses, this paper uses accuracy as the fitness function

(3) BFS-DELM methodology

According to the coding method and fitness function, the steps of the deep limit learning machine prediction method based on the BFS algorithm are as follows:

Step 1: The raw data is preprocessed and normalized into a test set and training set;

Step 2: The BFS algorithm encodes the initial parameters of the DELM and also initializes the algorithm parameters, such as the population parameters and the number of iterations, and calculates the value of the fitness function;

Step 3: Update the strategy using the Flight Search Behavioral Stage, Domain Behavioral Stage, and Cognitive Behavioral Stage;

Step 4: Calculate the fitness function value and update the global optimal solution and individual optimal solution;

Step 5: Judge whether the termination condition is satisfied. If satisfied, exit the iteration, output the optimal network parameters, and execute step 6; otherwise, continue to complete step 3;

Step 6: Decode the parameters of the BFS-based optimization network to obtain the hidden layer unit weights and biases of the deep limit learning machine network;

Step 7: Construct the BFS-DELM network, train the network using the training set to get the prediction model, and input the test set into the prediction model to get the prediction results.

5. Experiments and analysis of results

To validate the performance of the multi-dimensional innovative teaching quality evaluation method proposed in this paper, the assessment results of the proposed algorithm are analyzed and discussed in this section by selecting the intelligent teaching evaluation data.

5.1 Simulation Environment Setting

In this paper, MATLAB 2021a is used to write the program, and the test environment is a Windows 10 system. The experimental dataset is selected as the training set of the evaluation model, and the intelligent teaching evaluation data in the first half of 2023 is used as the test set of the assessment model. The specific parameter settings of the philosophical teaching quality evaluation method are shown in Table 1.

Table 1 Parameter settings of clever teaching quality evaluation methods

| arithmetic	parameterization
SVM	C=100,σ=0.1
ELM	The hidden layer node is 50, and the activation function is the radial basis function.
BP	Number of input nodes 35, number of intermediate nodes 70, number of output nodes 1
BFS-BP	The number of population sizes is 50, and the network parameters are set as in BP.
DELM	Two hidden layers with the number of nodes in each layer 10, 10
BFS-DELM	The population size is taken as 50, and two hidden layers with the number of nodes in each layer as 10, 10

5.2 Analysis of assessment results

To validate the performance of the proposed evaluation method in this paper, the evaluation results of the proposed algorithm are analyzed and discussed in this section by selecting the Smart Teaching Evaluation dataset.

To verify the validity of the model proposed in this paper, BFS-DELM is compared with the other five models, and the assessment results and relative errors of each model are shown in Figure 6. By comparing the evaluation results in Figure 6, the evaluation results of BFS-DELM are closer to the actual values, thus indicating that the performance of the BFS-DELM evaluation model is better than that of the SVM, ELM, BP, BFS-BP, and DELM models; by comparing the evaluation results in Figure 6(e) and (f), the BFS algorithm can search for better parameters of the DELM network, which leads to a further improvement in the evaluation performance.

From the relative errors in Figure 6, it can be seen that the BFS-DELM assessment model assessment error is in the range of 0.02, the SVM assessment model assessment error is in the field of 0.1, the ELM assessment model assessment error is in the range of 0.1, the BP assessment model assessment error is in the range of 0.1, the BFS-BP assessment model assessment error is in the field of 0.1, and the DELM assessment model assessment error is in the range of 0.05 range. In summary, the BFS-DELM assessment model error is the smallest overall.
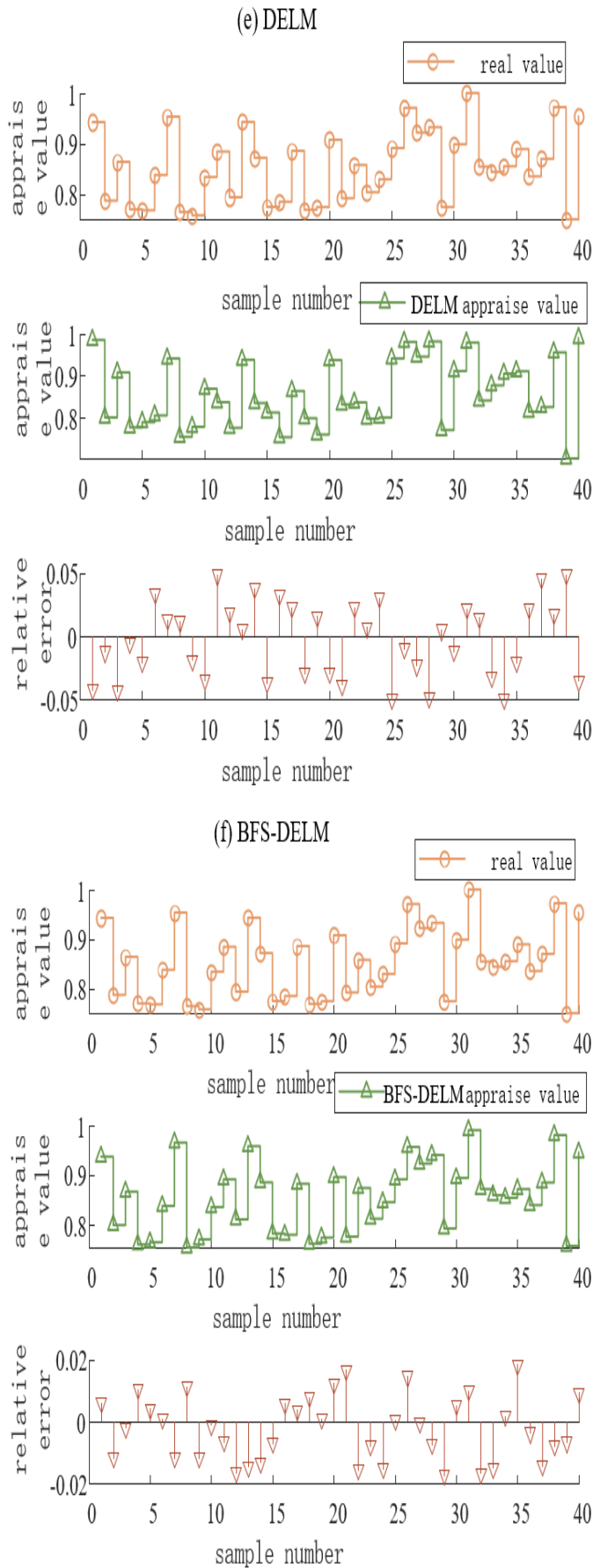
(a) SVM

(b) ELM

(c) BP

(d) BFS-BP

(e) DELM

(f) BFS-DELM
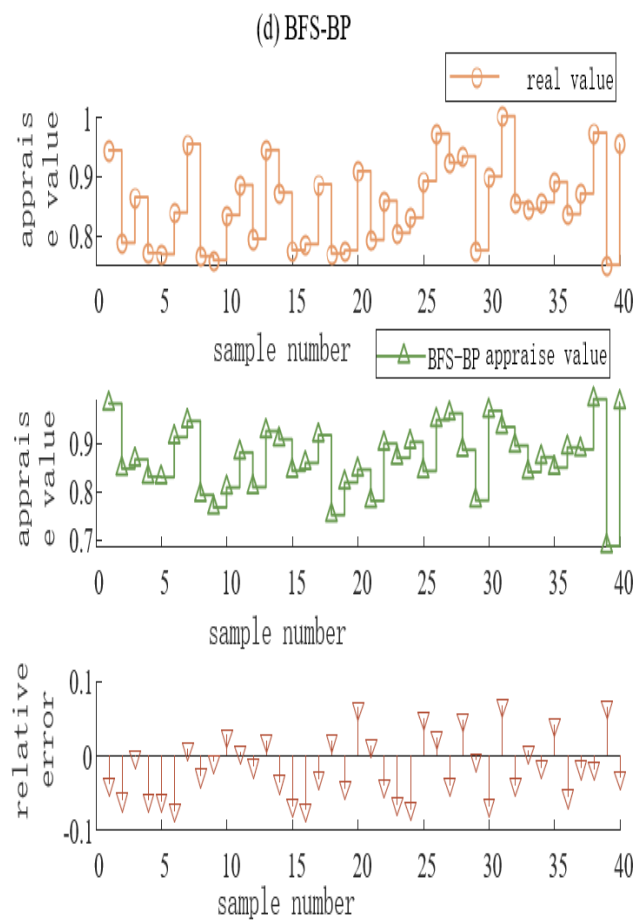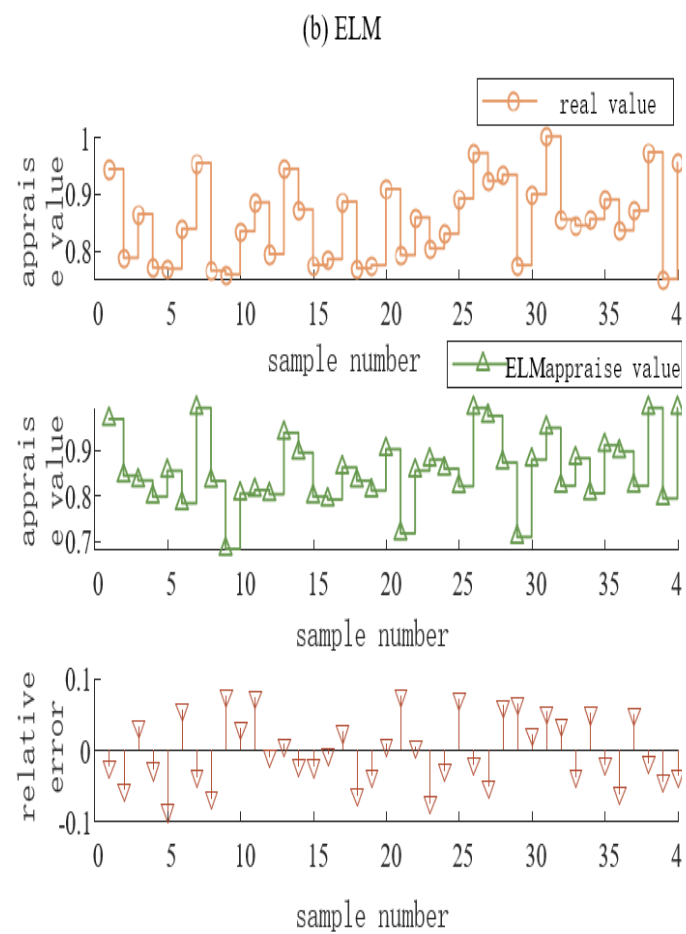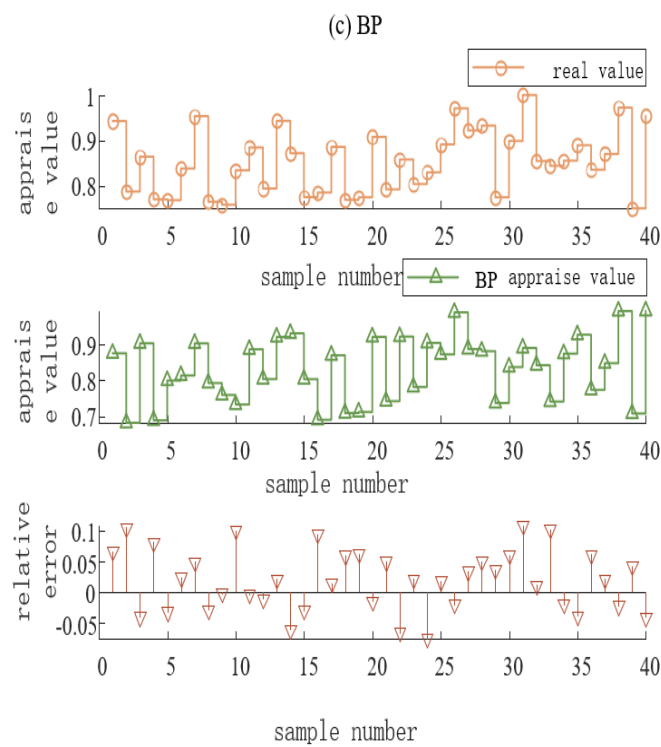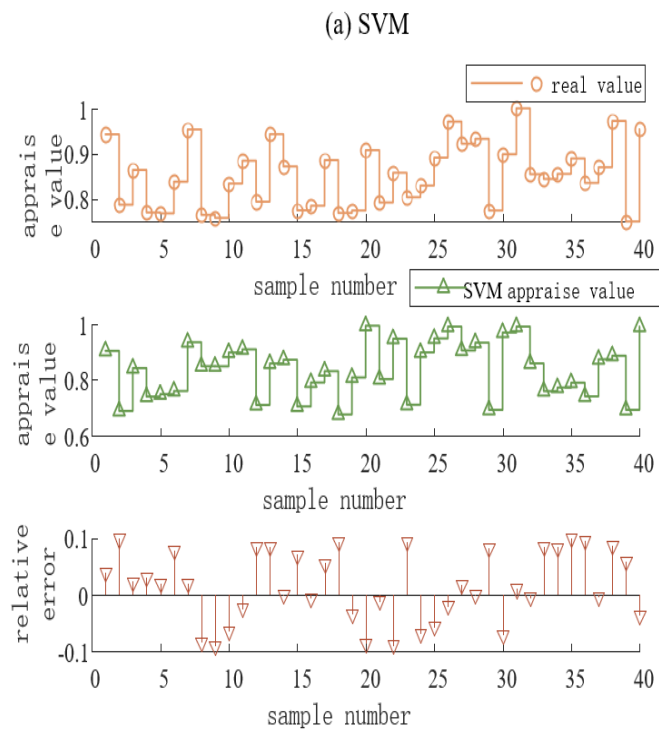
Figure 6 Comparison of the actual value of the assessment of teaching quality and the results based on each methodology

6. Conclusion

Aiming at the current teaching quality evaluation method with low precision, this paper proposes an innovative approach based on the intelligent optimization algorithm to optimize the depth limit state machine network. The method constructs a multi-dimensional innovative teaching evaluation system by analyzing the influencing factors of teaching quality evaluation and optimizing the deep limit state machine network using the BFS algorithm to build a multi-dimensional brilliant teaching quality evaluation method. The simulation experiment shows that the DELM assessment model based on BFS optimization is not only better than other assessment models in terms of assessment accuracy. Due to the poor robustness of the proposed assessment model, further improving the BFS-DELM assessment stability is the following research focus.

7. Acknowledgements

References

[1] Neuroscience C I. Retracted: English Teaching Quality Evaluation Based on Analytic Hierarchy Process and Fuzzy Decision Tree Algorithm[J]. Computational intelligence and neuroscience, 2022.

[2] Qiao Y. Optimization of Teaching Quality Evaluation System for Management Majors in Application-oriented Undergraduate Universities[J]. Journal of International Education and Development, 2022.

[3] Wang Q . Research on teaching quality evaluation of college English based on the CODAS method under interval-valued intuitionistic fuzzy information[J].Journal of Intelligent and Fuzzy Systems, 2021:1-10.

[4] Jiang H, Liu Y. Construction of Teaching Quality Evaluation System of Higher Vocational Project-Based Curriculum Based on CIPP Model[J]. EJournal Publishing, 2021(6).

[5] Panayiotou A, Herbert B, Sammons P, et al. Conceptualizing and exploring the quality of teaching using generic frameworks: a way forward[J].Studies In Educational Evaluation, 2021, 70(3):101028.

[6] Raffaghelli J E, Grion V, Rossi M . Data practices in quality evaluation and assessment: two universities at

a glance[J].Higher Education Quarterly,. 2023, 77(1):7-26.

[7] Qianna S . Evaluation model of classroom teaching quality based on improved RVM algorithm and knowledge recommendation[J].Journal of Intelligent and Fuzzy Systems, 2021, 40(2):2457-2467.

[8] Wang C, Zheng P, Zhang F, et al. Exploring Quality Evaluation of Innovation and Entrepreneurship Education in Higher Institutions Using Deep Learning Approach and Fuzzy Fault Tree Analysis[J].Frontiers in Psychology, 2022.

[9] Zhang N, Tan L, Li F, et al. Development and application of digital assistive teaching system for anatomy[J].Virtual Reality & Intelligent Hardware, 2021, 3(4):315-335.

[10] Shuai L, Yunxia X, Lyuhui S, et al. Research Progress of Application of Bacillus subtilis as Feed Additive in Pigs Production[J].Chinese Journal Of Chinese Journal Of Animal Nutrition, 2022, 34(4):2105-2113.

[11] Li X . A new evaluation method for English MOOC teaching quality based on AHP[J].International Journal of continuing engineering education and Life International Journal of continuing engineering education and life-long learning, 2022(2):32.

[12] Wang Q . Research on teaching quality evaluation of college English based on the CODAS method under interval-valued intuitionistic fuzzy information[J].Journal of Intelligent & Fuzzy Systems: Applications in Engineering and Technology, 2021(1):41.

[13] Chen Y . College English Teaching Quality Evaluation System Based on Information Fusion and Optimized RBF Neural Network Decision Algorithm[J]. Journal of Sensors, 2021.

[14] Chen X . Design of a Hybrid Classroom Teaching Quality Evaluation System Based on Information Technology[J].Journal of Physics Conference Series, 2021, 1852(3):032025.

[15] Hou J . Online teaching quality evaluation model based on support vector machine and decision tree[J].Journal of Intelligent and Fuzzy Systems, 2021, 40(2):2193-2203.

[16] Yuan T. Algorithm of Classroom Teaching Quality Evaluation Based on Markov Chain[J]. Complexity, 2021, 2021(21):1-12.

[17] Shan P, Xinyi Y . Deep Convolutional Extreme Learning Machine and Its Application in Handwritten Digit Classification[J].Computational Intelligence & Neuroscience, 2016, 2016:1-10.

[18] Hou J . Online teaching quality evaluation model based on support vector machine and decision tree[J].Journal of Intelligent and Fuzzy Systems, 2021, 40(2):2193-2203.

[19] Wu F, Fang Y. Multilevel Evaluation of Teaching Quality in Higher Education Using Single-Valued Neutrosophic Set[J]. Mobile Information Systems, 2022.

[20] Liang J . Problems and Solutions of Art Professional Service Rural Revitalization Strategy Based on Random Forest Algorithm[J].Wireless Communications and Mobile Computing, 2022, 2022(1):1-11.

[21] Wenming H. Simulation of English teaching quality evaluation model based on Gaussian process machine learning[J]. Journal of intelligent & fuzzy systems:

applications in Engineering and Technology, 2021, 40(2).

[22] Qi S, Liu L, Kumar B S, et al. An English teaching quality evaluation model based on Gaussian process machine learning[J]. Expert systems: The international journal of knowledge engineering, 2022.

[23] Zhang K H H. Birds foraging search: a novel population-based algorithm for global optimization[J].Memetic computing, 2019, 11(3).

[24] Navarro A B , Bogoni J A , Moreira M Z ,et al. Intraguild niche partitioning in granivorous birds from the late past[J].Avian Research, 2023, 14(1): 100075-100075.