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Article

Research on the Design of Computer-Assisted Learning System and Learning Effect Evaluation for Higher Vocational English Education

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Abstract: With the deepening of globalization, there are more and more international exchanges, and English has become an important medium of communication, so how to improve the effect of higher vocational English education has become the focus of research in the field of education. To this end, the article designs a personalized recommendation system for English teaching resources based on deep learning. The system matches user features and English learning resource features through neural network to complete resource recommendation. At the same time, the article establishes a learning effect prediction model based on IGWO-CNN, uses the improved Gray Wolf algorithm to optimize the hyperparameters of the convolutional neural network, and finally carries out performance comparison experiments on the model. In the accuracy index comparison, this paper's algorithm grows more stable, the value is maintained between 0.2~0.3, the growth rate is not more than 0.1, that is, the learning resources recommendation algorithm proposed in this paper has high stability, the best recommendation performance, and can be good for students to recommend learning resources. This paper's algorithm optimizes the CNN network of higher vocational English teaching quality evaluation model on the test set of data evaluation error is not greater than 0.01, compared with the evaluation error of other evaluation model methods is smaller. From the experimental results, it can be concluded that the algorithm in this paper is highly accurate and less time-consuming, and can effectively evaluate the quality of English teaching in higher vocational English education.

Keywords: IGWO-CNN; Gray Wolf Algorithm; Convolutional Neural Network; Learning System; Higher Vocational English

1. Introduction

With the further development of economic globalization, China's accession to the WTO, the deepening of reform and opening up and the hosting of the 2008 Olympic Games, the society will provide graduates of higher vocational colleges and universities with more opportunities for foreign-related activities. Higher vocational students, who also belong to the elite class of the society, will work as front-line professionals in the fields of tourism, aviation, electronics, textile, clothing, construction and other economic and information fields on their own [1-3]. At the same time, they also hold the mission that cannot be underestimated, that is, to use English as a language tool in foreign communication to fully disseminate Chinese culture, so that foreigners can really appreciate the profound Chinese national culture from various fields [4].

However, in the actual teaching of English culture, both teachers and students still have many misunderstandings. On the one hand, due to teachers' one-sided understanding of the guiding ideology of “practicality-oriented and sufficient” in the “Basic Requirements for English Courses for Higher Vocational Training” [5], they even think that English for higher vocational training is easier than undergraduate courses, and the requirements are lower than those for undergraduate courses, thus lowering the standard of English teaching and focusing on the teaching of basic knowledge and the cultivation of test-taking ability only [6-7]. On the other hand, in the limited cultural teaching, the local culture is almost ignored, and the students lack a deep understanding of the Chinese culture, even the simplest and most traditional Chinese culture cannot be described in English, which leads to "aphasia" in international communication [8-10]. In terms of assessment of learning effectiveness, many high school students are unable to use English to describe the content of traditional Chinese culture. In terms of learning effect assessment, English education in many higher vocational colleges and universities has been following the practice of general undergraduate colleges and universities in China, and most of the English education in higher vocational colleges and universities is taught and assessed in the form of book teaching and paper examination results [11-13]. Under this teaching and assessment system, students repeat memorizing English words, doing English test papers, and learning English for the sake of exams. The current teaching status quo of English education in higher vocational colleges and universities has seriously inhibited students' motivation to learn and neglected the improvement of students' practitioner skills, as a result of which the overall teaching level of English teachers has declined [14]. Therefore, how to stimulate the learning motivation of English education in higher vocational institutions and improve the skills necessary for students' future employment is an important problem that needs to be solved in English education in higher vocational institutions at present.

Computer-assisted instruction (CAI) generally refers to all types of computers and related technologies in teaching and learning, such as desktop computers, tablets, cell phones, multimedia technologies, etc., and the use of computer-assisted instructional tools can assist the learners in their English learning in many ways, such as e-annotations, subtitles, apps, etc. [15] An empirical study by Xie, C[16] found that, after the teachers adopted CAI, the students' English composition error rate was significantly reduced, while the overall English grade increased from 58.6% to 69.6%, these results confirm the effectiveness of CAI applied to English education. Sharifi, M et al [17] systematically conducted a meta-analysis of 140 studies on CAI and language teaching and learning, and the study found that CAI has an overall moderate effect on English language development, with a weighted mean achievement effect size of +0.50, while web-based instruction had a larger mean effect (+0.54) than traditional CAI. Gilakjani, A et al [18] explored the effectiveness of CAI in teaching English pronunciation and found through the results of a quantitative study that the English pronunciation of learners in the experimental group who received teacher-provided Computer-Assisted Pronunciation Teaching (CAPT) education was significantly improvement.

The use of massive resources as well as computer-assisted personal independent learning has become a common phenomenon, compared with the traditional mode of learning, with the assistance of CAI learners are able to study more conveniently after their busy schedules, and at the same time they are also able to utilize massive resources on the Internet for effective learning. Asrifan, A et al.[19] used a non-equivalent control group design to investigate the impact of computer-assisted language learning (CALL) on English achievement and attitudes towards learning English and found that it had a significant effect on both English achievement and attitudes towards learning English. Tafazoli, D et al [20] explored the attitudes of English language learners towards CALL with a sample of 415 students.Descriptive statistics and non-parametric analysis found that learners had an accepting attitude towards CALL and that There was no significant difference in the attitudes towards CALL among learners of different origins.A study by Cetinkaya, L and Sütçü, S [21] showed that students who learned English vocabulary through a mobile vocabulary learning application in CAL performed significantly better than those who learned using the same paper-based materials.

And in the current research related to computer-assisted language learning systems, Lin, Y et al [22] proposed a computer-assisted learning expert system (CAL-ES) based on an expert system, which specifically includes four mechanisms, namely, knowledge representation, knowledge acquisition, knowledge organizer, and knowledge miner. Choi, S et al [23] proposed a combination of a chatbot and a dialogue system for a computer-assisted English learning system with free communication by topic, the average success rate of the system's dialogue rounds is 80.86%, which enables correction of learners' English grammatical errors. Tian, C [24] developed a computer-assisted language learning system that uses Long Short-Term Memory (LSTM) network to provide learners with a personalized and efficient learning experience, while at the same time improving their English language skills through a dynamic learning models and adaptive learning paths to improve learners' mastery of English syntactic structures. Troussas, C[25] combined fuzzy string search and string interpretation similarity algorithms for misconceptions detection and identification (MDI), and embedded MDI into an adaptive and intelligent e-learning system for second language acquisition, thus realizing the provision of personalized learning for learners to meet their needs. Jing, Y [26] proposed the design and framework of an English assisted learning system based on deep learning and data analysis techniques, which uses intelligent algorithms to assess and analyze students' language abilities in vocabulary, pronunciation, grammar, etc., and provides personalized teaching content and suggestions according to learners' learning situations, which improves students' motivation to learn to a certain extent. Huang, X [27] proposed a personalized mobile English learning system based on Android system and vocabulary learning, which consists of modules such as remote management server, client mobile learning, etc., to develop a new auxiliary learning method and tool for English learners.

Despite the fact that the use of CAL in English language teaching is becoming more and more normalized, little research has been done on the assessment of learning effectiveness in CAL learning environments. Traditional learning effectiveness assessment methods, such as test paper grades and teacher evaluation, may not be able to accurately assess the actual learning effectiveness of students in CAL learning environments, due to the fact that CAL learning environments accommodate more complex interactive and contextual learning [28-30]. For this reason, Shang, W [31] designed an English classroom teaching effectiveness assessment method based on machine learning and IoT technology, which effectively solved the problem of mismatch between assessment and teaching in CAL learning environments.Jing, Y et al [32] proposed a model for assessing the effectiveness of English language education based on big data analysis technology, and the results of the study showed that the assessment error range of the model was between 0.78%- 1.44%, all of which meet the requirements of English education learning effect assessment. With the synergy of big data analysis, machine learning and other technologies, the learning effect assessment method in CAL scenarios is able to capture the dynamic changes in learner behavior, mine a large amount of interactive behavioral data, and uncover the key elements that affect learning outcomes.

In this paper, a personalized recommendation system for higher vocational English teaching resources based on deep learning is first designed to obtain user behavior data and English teaching resources data through crawler technology, extract the features of the two and integrate them. The deep learning model is used to establish the association between user behavioral features and English teaching resources features to achieve personalized recommendation, and the effectiveness of the algorithm is verified using the corresponding experiments. Further, an optimized convolutional neural network (CNN) based on the Improved Gray Wolf Algorithm (IGWO) is proposed, which improves the Gray Wolf Algorithm by adopting dynamic convergence, reduces the global search speed by a nonlinear convergence factor, avoids the problem of the traditional Gray Wolf Algorithm falling into the local optimal solution, and searches for the optimal network of the CNN with the improved Gray Wolf Algorithm, and successfully avoids the CNN network structure's Uncertainty. Subsequently, the English learning effect evaluation model is established, and the existing evaluation indexes are screened and selected by principal component analysis. Finally, performance comparison experiments are carried out on the established English learning effect evaluation model.

2. Design of Personalized Recommendation System for Higher English Teaching Resources

The recommender system analyzes the user's preference through the user's historical behavior and gives suggestions to the user to select the materials and assists the user in the selection of teaching materials. The objectives to be met by the system in this paper are as follows: Objective 1: The system should have a fast processing capability to cope with a large amount of user behavior data analysis. Objective 2: The system should have a good ability to handle concurrent requests, support multiple clients to log in at the same time, and provide personalized recommendation services for multiple users at the same time. Objective 3: The system should have a good interactive interface, which is convenient for users to operate and browse. Objective 4: The system should have excellent scalability and support the expansion of recommendation algorithms to ensure that it meets the needs of users as they continue to grow.

2.1. Overall system framework design

Java EE multilayer structure has the characteristics of stability and scalability, and can realize information security processing, etc. For this reason, this paper designs the system logical architecture based on JavaEE multilayer structure. The architecture contains four layers, and the four-layer architecture of the JavaEE-based system is shown in Figure 1.

(1) Persistence layer. The persistence layer is connected to the database, and its main role is to persist the data about user behavior and higher vocational English teaching resources in the database to each business processing module, providing data for business processing.

(2) Service Layer. The service layer mainly provides personalized services for users, including information uploading/downloading, information management, personalized information customization, and targeted information query.

(3) Web layer: The Web layer is mainly used to receive user requests and respond to them to realize data interaction.

(4) Application layer. The application layer is also called the client layer, which can provide a platform for the client to preview and download higher vocational English teaching resources online, and can also display the recommendation results in the application layer.

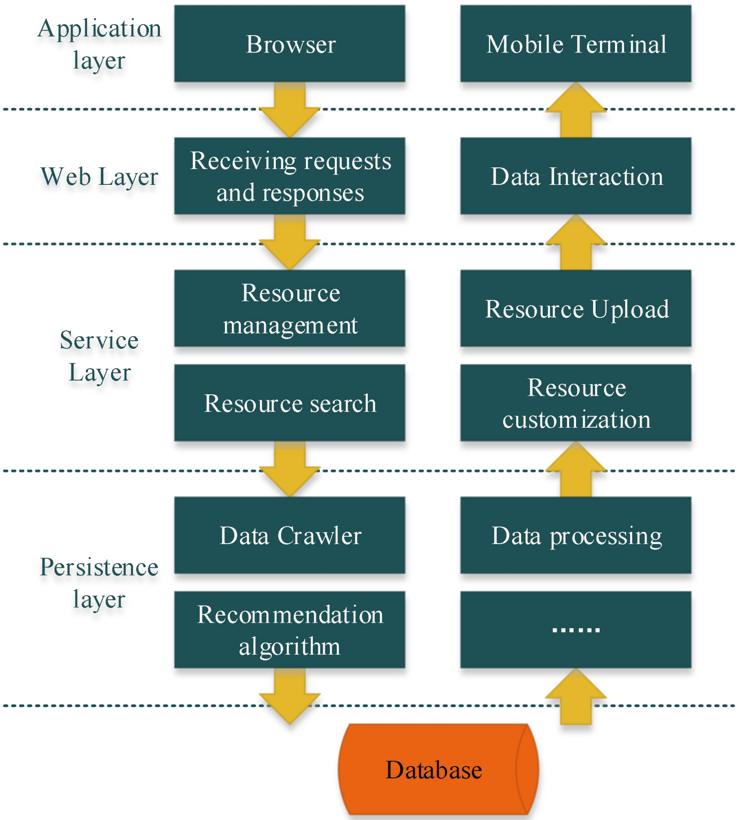


Figure 1. A four-tier system architecture based on JavaEE.

2.2. System Hardware Design

System hardware refers to the physical equipment that constitutes a computer and is the carrier for the operation of logical programs. In the designed deep learning-based personalized recommendation system for higher vocational English teaching resources, the key hardware used includes data collector, memory, and master controller.

2.2.1. Data collector

The data collector is a programmable logic chip equipped with a crawler program, which can be used to complete the search and collection of the user's historical learning data, including web browsing information, keywords searched by the user, records of resource downloads, communication and interaction information, and other data that can be used to understand the user's preferences [33]. The programmable logic chip in this system is EPM240T100I5N TQFP-100 CPLD.

2.2.2. Memory

The massive amount of higher vocational English teaching resources as well as a large amount of historical user behavior data are completely insufficient to be stored by the storage space of the system itself, so after the data collector completes one collection task, it needs to transfer the collected data to the external memory. The memory in this system is a 12-bit disk array, equipped with a 4-bit AnnapurnaLabsAlpineAL-324ARM@Cortex@-A57 quad-core 1.8GHz processor and 46BDDR4 memory (rechargeable up to 16GB), supporting SATA 6 GB /s hard disk transfer interface. Offer faster read and write speeds. In addition, the disk array has two 10GBESFP+ and two 2.5GBE network ports built-in. The disk array can be deployed in a reasonable network environment, thus realizing the replication, preservation and repair of massive data.

2.2.3. Master controller

The main controller is the core hardware of the system, which can control the overall operation of the system and the operation of various business logics. The main controller in this system is DTB-1022 J1900 embedded industrial computer.

2.3. System software design

System software is the logical running program of the system. In the software design, the most important thing is the design of each functional module. The various functional modules of the system, specifically, include the login module, the crawler collection module, and the recommendation algorithm module.

2.3.1. Login module

Before users can use the system, they need to gain access to the system, that is, they need to log in and register. When the user logs into the system for the first time, he/she needs to register an account and set a login password for the next time he/she logs in directly, and then go back to the login page and perform the login operation to access the system internally [34].

2.3.2. Crawler Collection Module

The crawler collection module mainly uses crawler technology to collect user learning behaviors as well as higher level English resources. Web crawlers are able to automatically crawl and collect the information in the database. Its principle is to send a request to the network node through the initial URL (Uniform Resource Locator) to gain access to the corresponding information, and then extract its IP address on the basis of parsing the content, and then re-enter the crawling queue after reorganizing the connection of the URL to form a new URL queue for a new round of crawling and the next round of crawling. Keep repeating the above process until the end conditions are met. The specific crawler acquisition process is as follows.

Step 1: Pick the seed URL.

Step 2: Put the seed URL into the queue.

Step 3: Crawl the information and parse it to get the host IP.

Step 4: Download the information according to the IP address.

Step 5: Store the downloaded information in the database.

Step 6: Remove the seed from the current queue and put it into the next queue to be crawled and start a new round of information crawling.

2.3.3. Recommendation Algorithm Module

The recommendation algorithm module is the core module of the system, which mainly constructs a personalized recommendation model through deep learning algorithms, establishes association rules between user characteristics and features of higher vocational English teaching resources, so as to realize the screening of resources. The personalized recommendation model is shown in Figure 2.

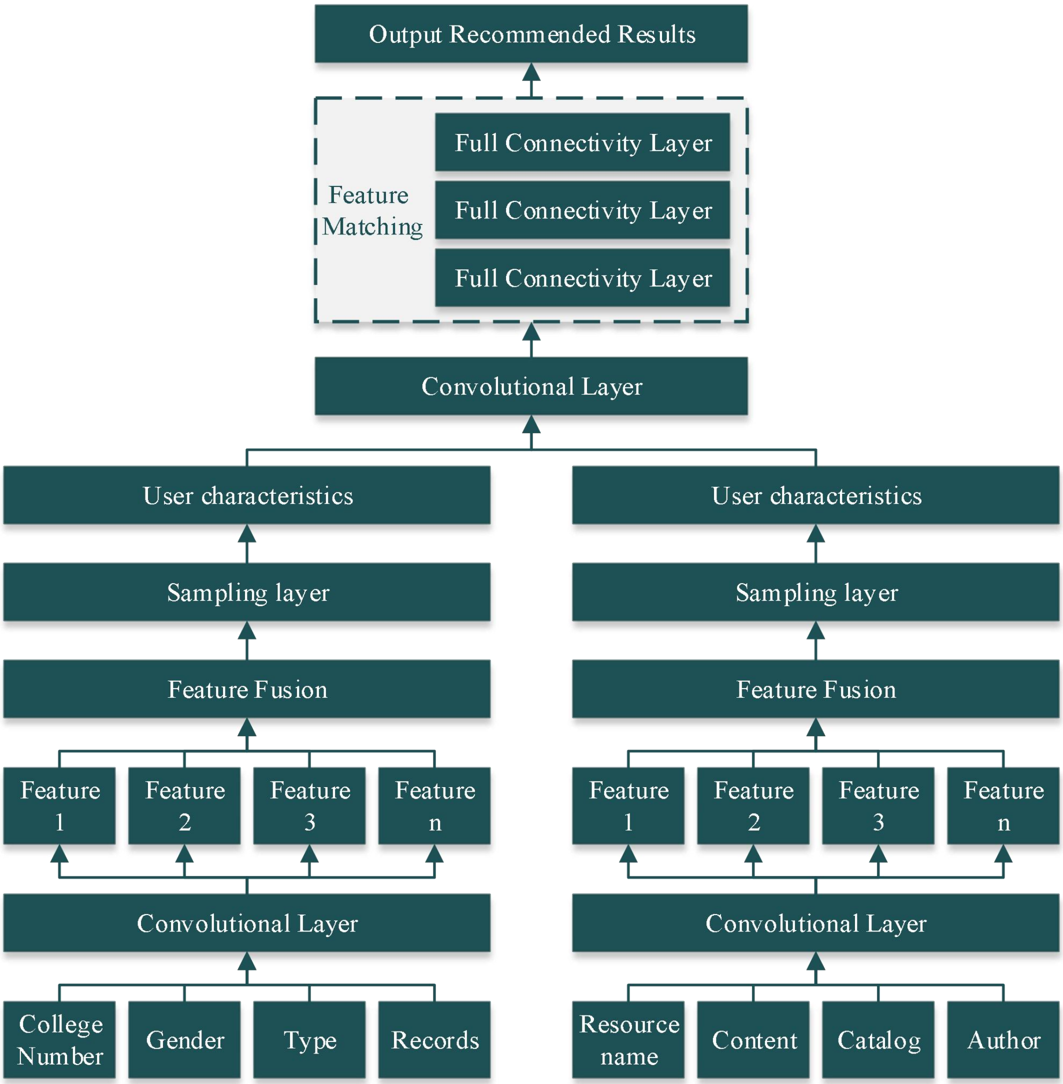


Figure 2. Personalized recommendation model.

There are various types of deep learning, in this module, we first choose one of them, convolutional neural network, to extract user features and features of higher vocational English teaching resources, and then these features are fused. The user features and higher vocational English learning resources features obtained by fusion are represented as follows:

$$u_i = \text{concatenate}(x) \tag{1}$$

$$b_i = \text{concatenate}(y) \tag{2}$$

Where x denotes the user feature information. u_i denotes the fused user feature information. y denotes the higher vocational English learning resource feature information. b_i denotes the fused higher vocational English learning resources feature information. The two are fused again and input into the multilayer neural network.

$$x_0 = \text{concatenate}\left(u_i, b_i\right) \tag{3}$$

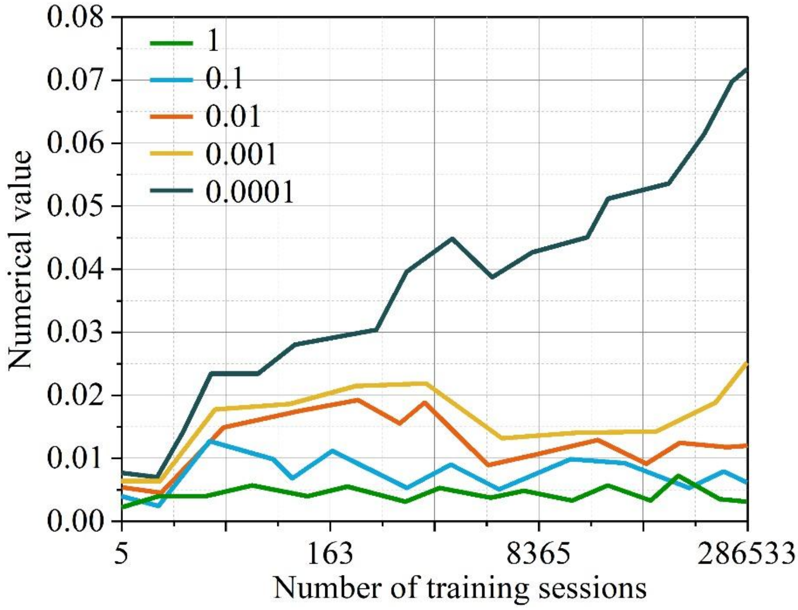
Where x_0 denotes the result of multiple fusion of user features and features of higher vocational English learning resources.

The user features and higher vocational English learning resource features are matched by neural network to complete the resource recommendation.

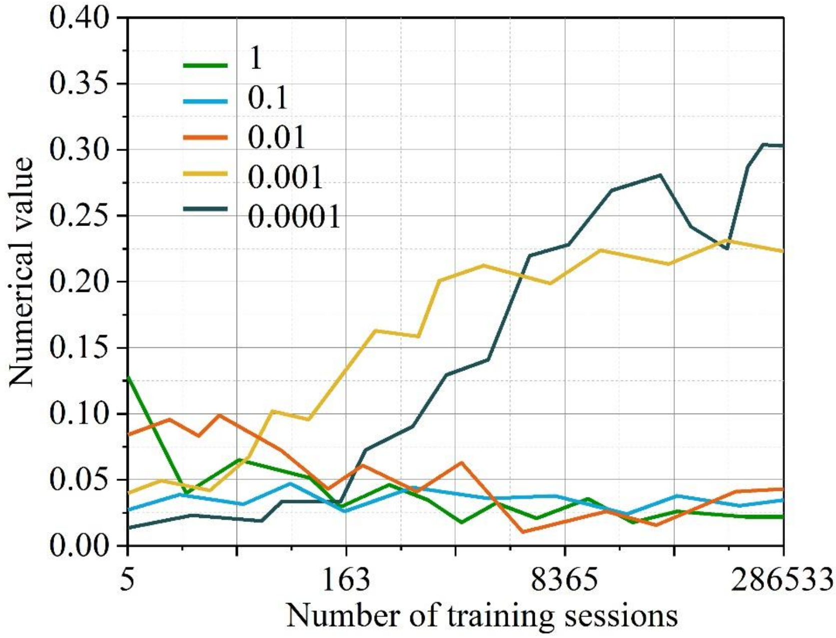
3. Analysis of the effect of recommending English education resources for higher education

In order to verify the effectiveness of the test question resource recommendation algorithm in the personalized recommendation system for English teaching resources proposed in the study, the study chooses comparative experiments for verification. The hardware environment of the experimental development is an Intel processor, the number of training times is set to 286533, the input vector dimension is set to 10, the hidden layer vector dimension is set to 18, and the output vector dimension is set to 1. During the training, it is necessary to adjust the parameters of the model accordingly, so the study mainly adjusts the learning speed, the abandonment, and the number of batch sizes accordingly, and utilizes the recall, the ability to successfully obtain the next item, the item coverage, and the normalized discounting to predict the next item in a short time, to determine the effectiveness of the proposed English teaching resources personalized recommendation system. Recall rate, the ability to successfully obtain the next item predicted by this method in a short period of time, the amount of item coverage, and the normalized discounted cumulative gain are used to judge the actual quality of the model, so as to decide the final construction of the model.

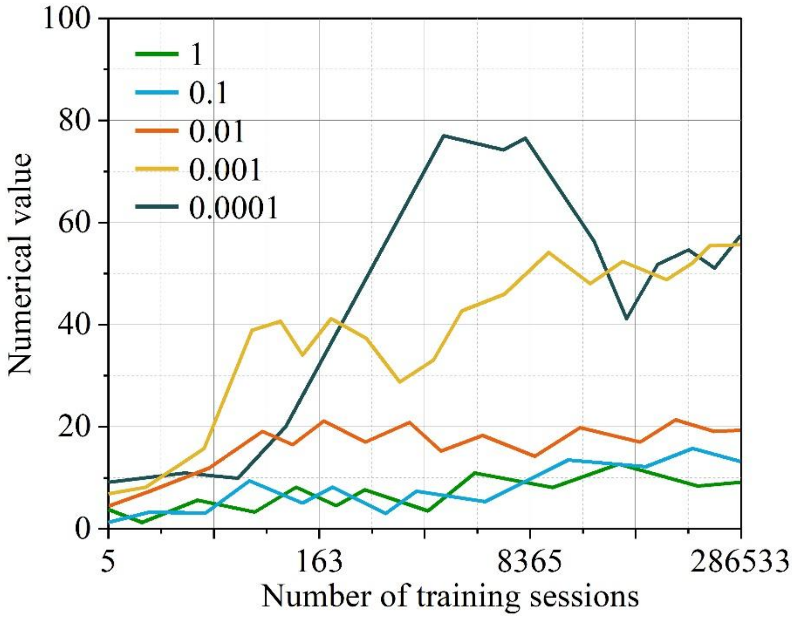
In the learning speed, the study selected the learning speeds of 0.0001, 0.001, 0.01, 0.1 and 1 for the comparison experiments, and the results of the four indexes under different learning speeds are shown in Fig. 3 (Figs. a~d are the results of the recall rate, the results of the sps, the results of the amount of item coverage, and the results of the NDCG, respectively, under different learning rates). The comprehensive figure can be seen that under the four indicators, the learning speed of 0.0001 is significantly better than other learning speeds, and with the growing number of training times recall rate has been rapidly improved, up to 0.072. Therefore, the study chooses 0.0001 as the learning speed of the final model of the study.



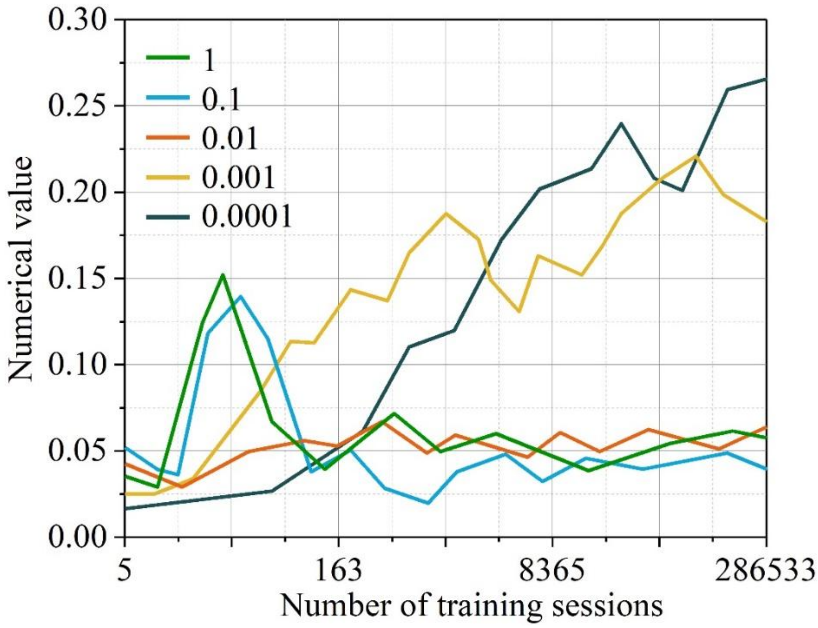
(a) Recall rate



(b) Sps



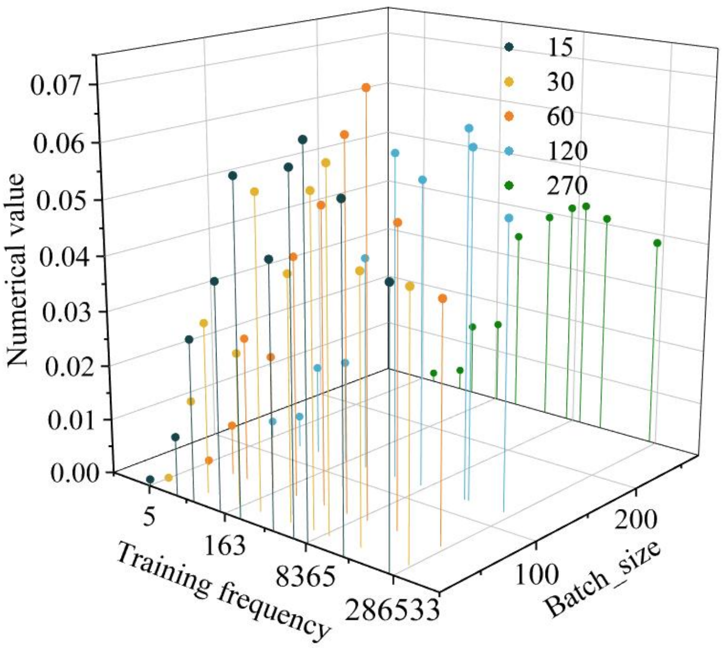
(c) Project coverage



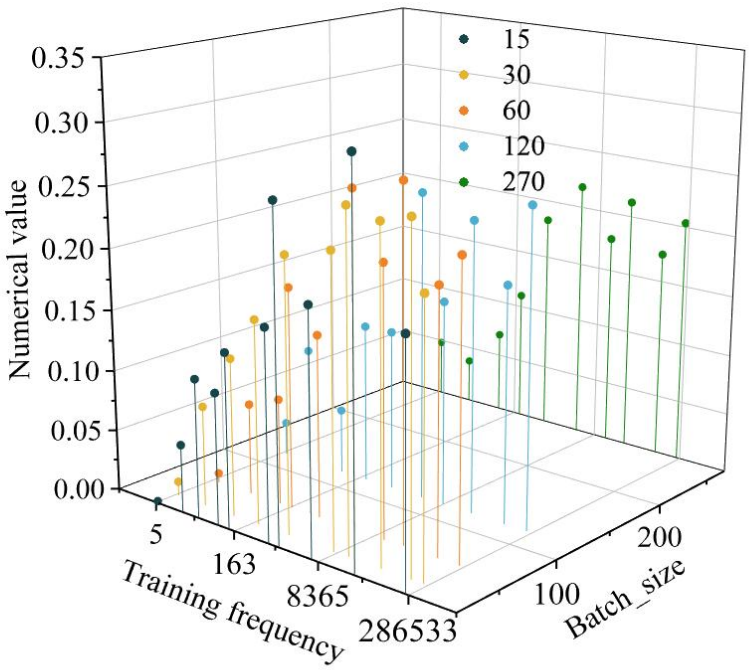
(d) NDCG

Figure 3. The results of four indicators under different learning speeds.

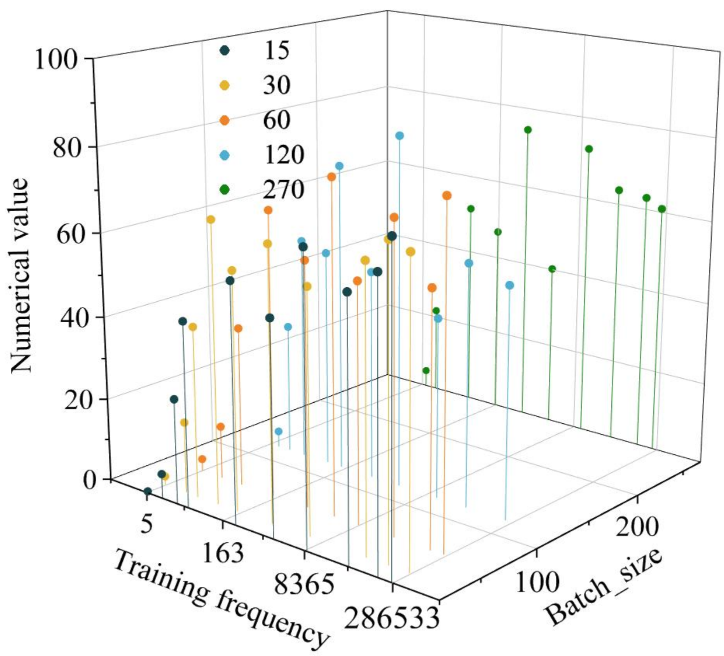
On this basis, in order to circumvent the fitting phenomenon of the research model in the actual training, the study introduced the Dropout parameter. When adjusting the parameters of Dropout, the study selected 0.4, 0.5, 0.6, 0.7 and 0.8 as the Dropout parameters for comparison experiments. After comprehensive consideration, the study chose 0.5 as the final Dropout parameter of the model. Meanwhile, in order to select the most suitable batch_size for the research experiment, the study conducted comparative experiments with batch_sizes of 15, 30, 60, 120, and 270 respectively. The results of the four indicators under different batch_size values are shown in Figure 4 (Figures a to d are the results under different batch_size values respectively) (Return rate results, sps results, project coverage results and NDCG results). As can be seen from the composite figure, different values of batch_size show similar trends in the first three indicators. Among them, when the batch_size is 270, the coverage of items in the training shows a surge and then tends to stabilize.



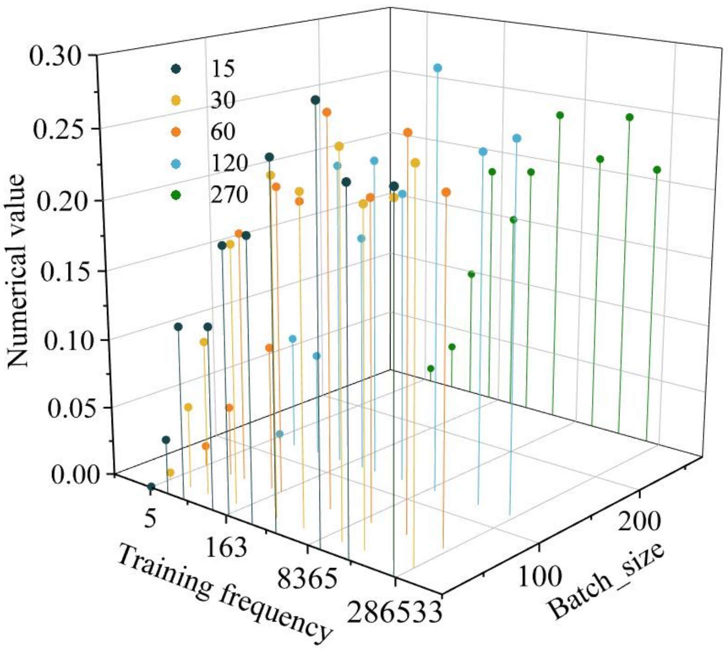
(a) Recall results under different batch_size parameters



(b) The sps results under different batch_size parameters



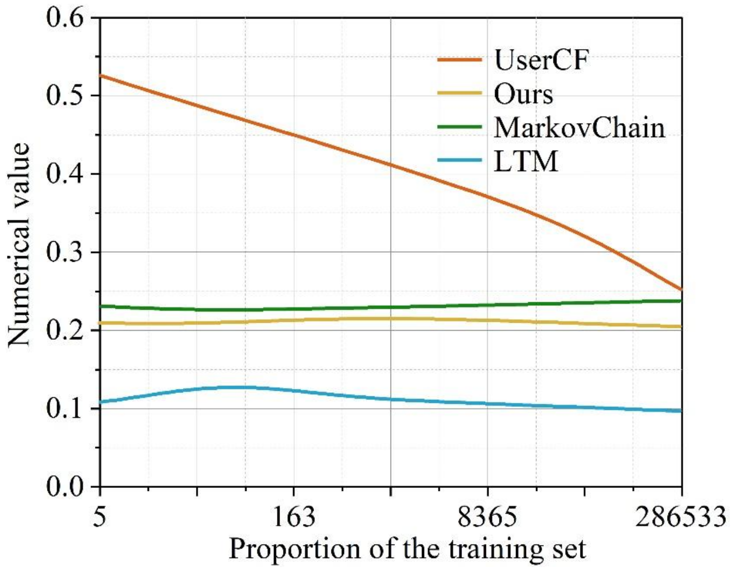
(c) The results of project coverage under different batch_size parameters



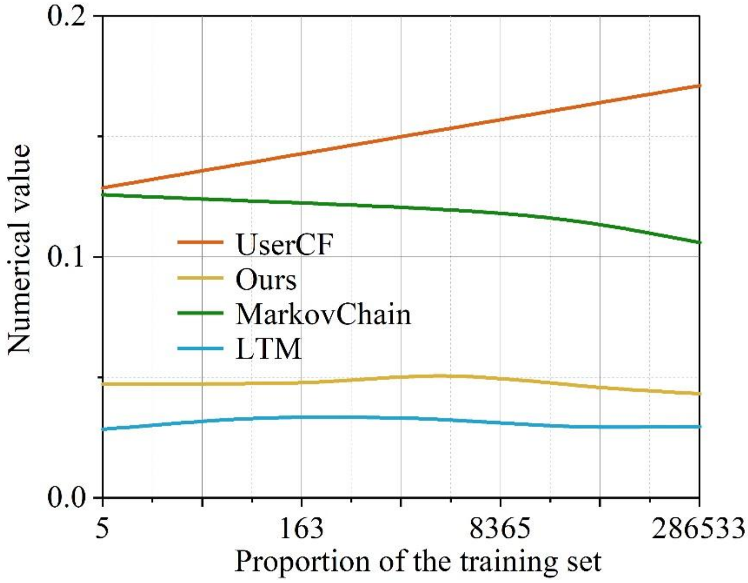
(d) The NDCG results of different batch_size parameters

Figure 4. The results of four indicators under different values of batch_size.

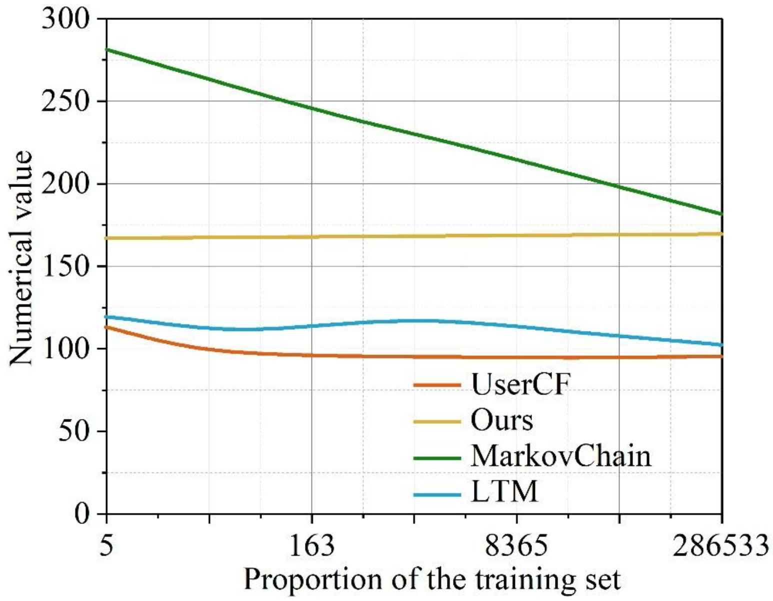
After considering the experimental results and stability factors, the study chooses 30 as the final batch_size value of the model. Therefore, the proposed algorithm model is constructed by inputting the learning speed, Drop-out and batch_size obtained from the experiments into the final model, and at the same time, the user-based collaborative filtering recommendation algorithm (UserCF), the latent trajectory modeling recommendation algorithm (LTM), and the Markov chain prediction algorithm are introduced, and compared with the proposed algorithm of the study. The comparison results of different algorithms under different metrics are shown in Fig. 5 (Figs. a~d show the accuracy results, recall results, item coverage results and AD results, respectively). The comprehensive figure shows that the growth of the research-proposed algorithm is more stable in the comparison of accuracy indexes, and the value is maintained between 0.2 and 0.3, and the growth is not more than 0.1. The UserCF algorithm shows an overall decreasing trend, its value is as high as 53.1 when the weight of the training set is 5, but it is lower than 25% when it is 286533. MarkovChain algorithm shows a decreasing and then increasing trend, and the overall growth rate is more than 0.2. In the recall comparison, the gradual increase in the proportion of the training set makes UserCF and MarkovChain algorithms show significant changes, with the former showing increasing recall and the latter showing a fluctuating decrease. While the proposed algorithm and LTM algorithm show a stable trend, the values are maintained between 0.04 and 0.06. In the comparison of project coverage, MarkovChain algorithm shows a rapid decrease in project coverage, UserCF algorithm and LTM algorithm show an obvious trend of decreasing and then increasing and increasing and then decreasing, while the proposed algorithm is obviously more stable, and the value is maintained in the range of 140~200. In the comparison of AD results, the proposed algorithm has the strongest overall stability and the smallest fluctuations. Comprehensively, the personalized learning resource recommendation algorithm proposed in this paper has high stability and the best recommendation performance.



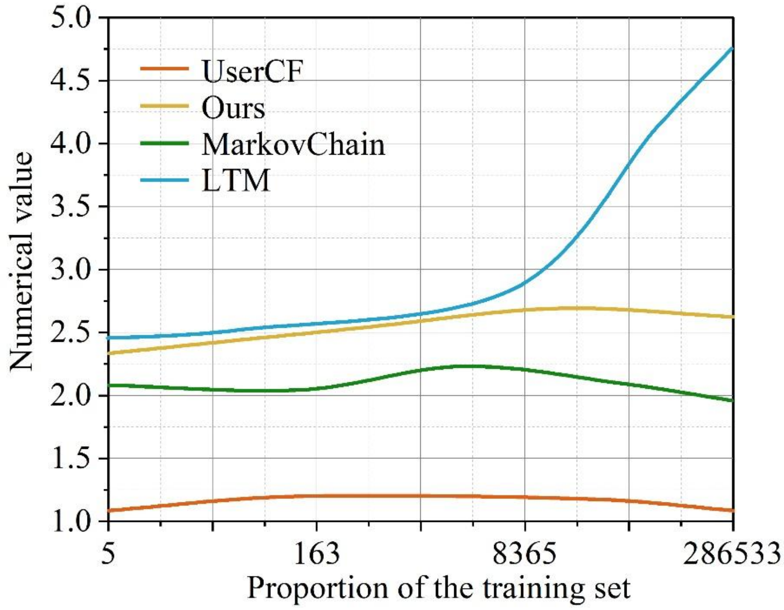
(a) Accuracy result



(b) Recall rate result



(c) Project coverage result



(d) AD result

Figure 5. The comparison results of different algorithms under different indicators.

In order to verify the recommendation effect of the adaptive learning system under the algorithm, the study analyzes its practical application, and the experiment looks for 100 and 800 bits to carry out two experiments, and the actual recommendation effect of the adaptive learning system is shown in Table 1. As can be seen from the table, the algorithm in the adaptive system under the actual operation of the 100 people test case not only the actual recommended response time of 4.5s, while the success rate of the recommendation is as high as 99.6%, indicating the effectiveness of this paper's algorithm.

Table 1. The actual recommendation effect of the adaptive learning system.

	Results of 100 experiments	Results of 800 experiments
Recommended response time	4.5s	26.9s
Throughput rate	24.2	20.6
The actual average time of the server request waiting	45.6ms	45.2ms

Concurrent number of times	100	800
Recommend the actual total number of responses.	100	800
The average latency time for user requests	4563.9ms	22596.3ms
Recommendation success rate	99.6%	99.2%

4. IGWO -CNN-based model for assessing English learning effect

4.1. IGWO-CNN Model

4.1.1. The Gray Wolf Algorithm

(1) Traditional Gray Wolf Algorithm

The traditional Gray Wolf Algorithm (GWO) is used to find the optimal solution of an optimization problem by simulating natural phenomena such as predation, competition and cooperation among individual gray wolves.

The implementation steps of the GWO algorithm are described as follows: determine the range of values of the parameters and randomly initialize the wolves within that interval. Calculate the fitness function values of all wolves and rank them. Select α, β, δ wolves according to the ranking of the calculated fitness function values. Perform the position update of the wolf. Update the parameters a, A, C. Determine if the result satisfies the fitness function requirements, if not, return to step 2 to reprocess. Output the current position of the α wolf as the optimal solution.

(2) Dynamic convergence factor improvement

According to the above description, it can be found that the GWO algorithm exists a contradiction between the global search and the local optimal convergence speed, and in GWO, the convergence factor (a) tends to decrease linearly, however, the convergence process of any good optimization algorithm cannot be linear, and GWO is no exception. Therefore, an exponential decision-making algorithm is chosen to control the convergence speed with the functional expression:

$$a = 2 - 2\left(2^{\frac{t}{\max}} - 1\right) \tag{4}$$

Where: t represents the number of iterations and max denotes the maximum number of iterations.

The rate of dimensionality reduction and the way of dimensionality reduction of the method are changed by the modification of the convergence factor. The curve of the improved convergence factor (a) shows an up-convex shape and its descending rate is gradually slowed down in the first half of the iteration, which indicates that the algorithm can find the alternative solutions more easily and possesses a stronger global search capability. And in the second half of the iteration, the rate of descent gradually speeds up, which indicates that the algorithm has stronger local search ability and can improve the convergence performance of the algorithm [35]. Therefore, this convergence factor realizes the balance between global search and local optimal convergence speed, which further improves the algorithm's global optimization ability and is more in line with the actual convergence process. In this paper, the improved gray wolf algorithm using the dynamic convergence factor is called the IGWO algorithm.

4.1.2. Convolutional Neural Networks

The basic structure of convolutional neural network (CNN) includes input layer, convolutional layer, pooling layer, fully connected layer, and output layer. The 3 core ideas of local connection, weight sharing and pooling operation are used to reduce parameters, speed up the learning rate and reduce the complexity of the algorithm.

(1) Convolutional Layer

Convolutional layer is the most important part of CNN, its input and output are connected by weights and bias. Convolutional layer its input-output correspondence is:

$$x_i^{out} = f\left(\sum_{i=1}^{n}\left(x_i^{in} \times W_{ij}\right) + b_j\right) \tag{5}$$

Where: x_i^{out} represents the output of the i th neuron, x_i^{in} represents the input of the i th neuron, f is the nonlinear excitation function, W_{ij} is the weights of the input signals to the neurons, and b_j is the output bias.

(2) Pooling layer

The pooling layer is located behind the convolutional layer and mainly includes maximum pooling and average pooling. Average pooling is to average the feature points in the neighborhood, and maximum pooling is to maximize the feature points in the neighborhood, the maximum and average pools are shown in Figure 6. The maximum pooling and average pooling functions can be expressed as:

$$y_i^{out} = f_{sub}\left(y_q^{in}, y_{q+1}^{in}\right) \tag{6}$$

Where: y_i^{out} represents the output value of the i th neuron, y_i^{in} represents the input value of the i th neuron, and f_{sab} is the maximum or average value of the function.

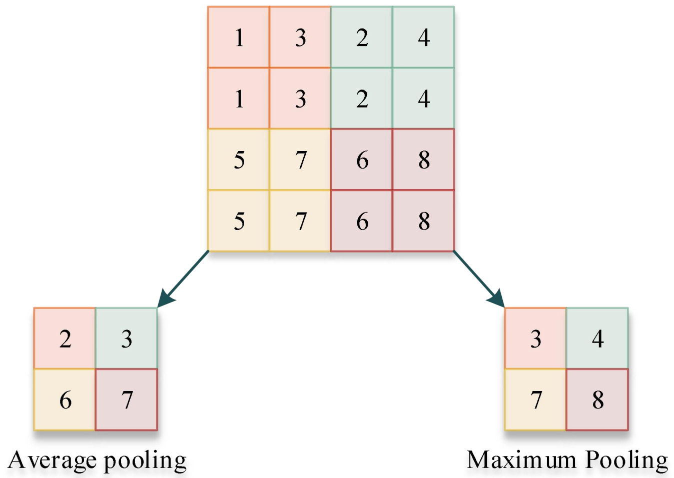


Figure 6. Maximum pool and average pool.

(3) Fully Connected Layer

The fully connected layer is behind the convolutional and pooling layers, and its role is to synthesize the features from the convolutional and pooling layers. Each neuron of the fully connected layer is fully connected to all neurons of the previous layer. The last fully connected layer connects all the features and sends the output values to the soft-max layer for classification.

4.1.3. IGWO Optimized CNN Network Architecture

In this paper, the IGWO **-**CNN method of IGWO optimization of CNN network structure is proposed for learning effect prediction.The IGWO-CNN optimization flow is shown in Fig. 7.

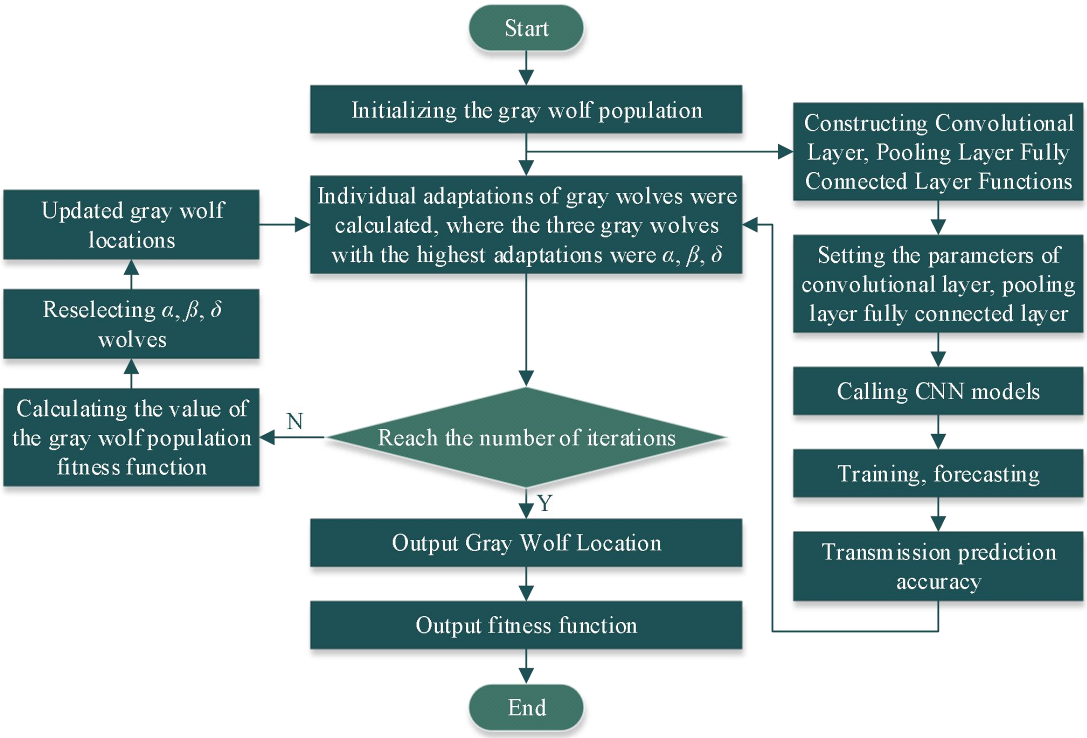


Figure 7. GWO-CNN optimization process.

4.2 Organization of the evaluation indicator system

In this paper, a questionnaire was distributed to the students of a higher education institution, and the data obtained from the questionnaire were processed using the method of principal component analysis in order to filter out the main evaluation factors that can reflect the learning effect. Since the questionnaire was coded in a 1-5 point scale, the data collected were all within the [1, 5] interval, which is equivalent to standardized processing, so after comparing the results of the processing of the results of the comprehensive considerations, the standardization of data is omitted here. Next, the data are converted into a matrix of correlation coefficients, and the correlation coefficients can be calculated by the arithmetic formula, and the matrix of correlation coefficients of the evaluation indicators is shown in Figure 8. The correlation coefficients between the two indicators related to the effect of learning motivation enhancement, namely the impact of learning interest and learning confidence, and the correlation coefficients between the two indicators related to the effect of learning convenience, namely the restriction of the interactive environment and the simplicity of the learning method, are high, which once again confirms that the data filled in by the respondents in the questionnaire survey are basically credible. And before extracting the principal components of the indicators, it is also necessary to test the data of the principal component analysis to determine whether the results obtained through the principal component analysis are accurate and valid. So while calculating the correlation coefficient, this paper tested the KMO of the correlation coefficient and partial correlation coefficient between the evaluation indexes, and the result of its test is 0.75, which meets the basic requirements of the principal component analysis method for data.

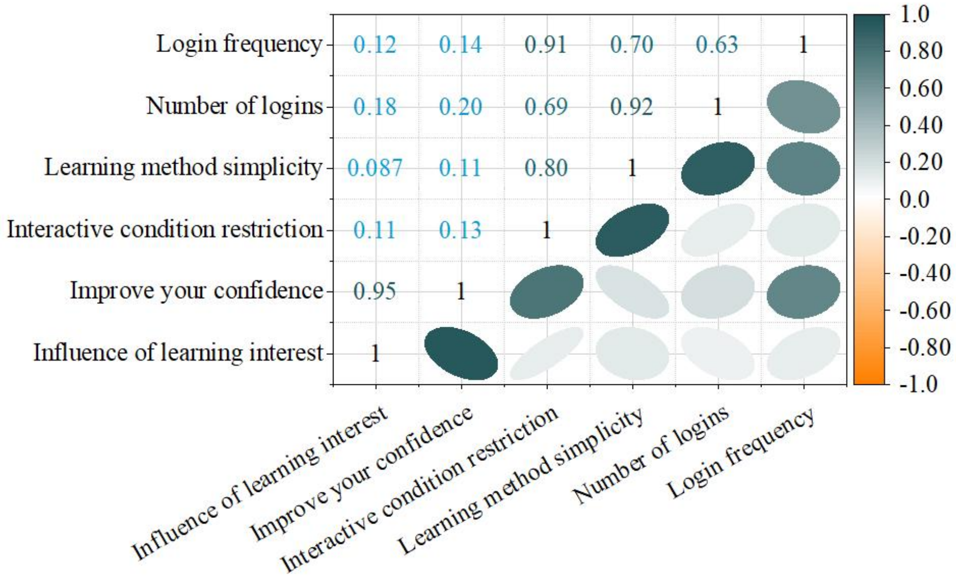


Figure 8. The correlation coefficient matrix of the evaluation index.

Therefore the next thing is to calculate the common factor variance of the evaluation factors, which is shown in Table 2. We got the correlation coefficient matrix consisting of 6 evaluation factors, so in order to extract the principal components, it is through the formula to be solved for the value of the characteristic equation. And calculate the vector of eigenvalues, that is, extract the variance value of the principal components, the size of the variance can reflect the influence of the component in the whole information, and according to the cumulative variance derived from the variance statistics can be more intuitive and clear understanding of the degree of information expressed by each component.

Table 2. Common factor variance.

Indicator name	Initial	Extract
The influence of learning interest	1	0.796
The improvement of learning confidence	1	0.871
The restrictive situation of interaction conditions	1	0.902
The simplicity of learning methods	1	0.869
Number of logins	1	0.792
Login frequency	1	0.761
Online duration	1	0.75
Average online duration	1	0.803
Match the time efficiency of teachers	1	0.92
Connect teachers' time efficiency	1	0.97
The difficulty of solving the problem	1	0.964
The breadth of problem-solving	1	0.942
Number of questions asked	1	0.854
Number of responses.	1	0.823
Has the problem been solved?	1	0.878
Whether the solution process is easy to understand	1	0.854
Video clarity	1	0.861
The fluency of communication	1	0.915
The time efficiency of problem-solving	1	0.927
Guidance fee	1	0.989
Communication expenses	1	0.923

The variance and cumulative variance corresponding to the eigenvalues can also be derived by using the formula, and the total explained variance is shown in Table 3. As can be seen from the table, there are a total of 4 eigenvalues greater than 1, with their values being 7.125, 6.32, 2.55 and 2.34 respectively. Moreover, the cumulative variance contribution rate of these eigenvalues also exceeds 85%, which meets the standard for extracting principal factors in the principal component analysis method. Therefore, these 4 principal components can basically summarize the effect of English learning. Become the principal component factor for evaluating the effectiveness of English learning.

Table 3. Explain the total variance.

Component	Initial eigenvalue			Extract the sum of squares and load it		
	Total	Variance (%)	Tired tree (%)	Total	Variance (%)	Tired tree (%)
1	7.125	33.929	33.929	7.125	33.929	33.929
2	6.32	30.095	64.024	6.32	30.095	64.024
3	2.55	12.143	76.167	2.55	12.143	76.167
4	2.34	11.143	87.31	2.34	11.143	87.31
5	0.64	3.048	90.358			
6	0.484	2.305	92.663			
7	0.393	1.871	94.534			
8	0.315	1.500	96.034			
9	0.202	0.962	96.996			
10	0.136	0.648	97.644			
11	0.123	0.586	98.23			
12	0.104	0.495	98.725			
13	0.064	0.305	99.03			
14	0.057	0.271	99.301			
15	0.054	0.257	99.558			
16	0.027	0.129	99.687			
17	0.026	0.124	99.811			
18	0.021	0.100	99.911			
19	0.011	0.052	99.963			
20	0.005	0.024	99.987			
21	0.003	0.014	100			

From the eigenvalues and variance contribution ratio, it can be known that there are a total of four principal components obtained here, but these four indicators are not individual indicators or new indicators appearing out of thin air, but a collection of indicators representing the significance of a number of indicators, which have corresponding coefficients in the collection to prove the status of the indicator in the evaluation of the main factor, so in order to derive the specific loading coefficients of each indicator in several principal components, the next step to be performed is the calculation of the factor loading matrix, and the learning effect component matrix is shown in Table 4. As shown in the principal component matrix of the table, the learning effect of higher vocational English education can be evaluated by these four principal component factors, which also represents the basic formation of the learning effect evaluation index system.

Table 4. Learning effect component matrix.

Indicators	List of principal components			
	1	2	3	4
The influence of learning interest	0.628	-0.097	-0.282	0.571
The improvement of learning confidence	0.538	-0.021	-0.372	0.672
The restrictive situation of interaction conditions	0.438	0.787	0.005	-0.223
The simplicity of learning methods	0.372	0.829	-0.164	-0.149
Number of logins	0.42	0.751	-0.206	-0.081
Login frequency	0.482	0.705	-0.009	-0.2
Online duration	0.705	-0.433	0.09	-0.136
Average online duration	0.694	-0.473	0.241	-0.213
Match the time efficiency of teachers	0.519	0.773	0.001	-0.237

Connect teachers' time efficiency	0.815	-0.525	0.189	-0.161
The difficulty of solving the problem	0.768	-0.51	0.19	-0.173
The breadth of problem-solving	0.384	0.851	-0.083	-0.2
Number of questions asked	0.615	0.039	-0.383	0.576
Number of responses.	0.628	0.145	-0.401	0.515
Has the problem been solved?	0.809	-0.412	0.191	-0.092
Whether the solution process is easy to understand	0.819	-0.401	0.126	-0.136
Video clarity	0.45	0.786	-0.051	-0.214
The fluency of communication	0.09	0.476	0.708	0.398
The time efficiency of problem-solving	0.819	-0.454	0.159	-0.193
Guidance fee	-0.01	0.474	0.8	0.382
Communication expenses	0.051	0.333	0.758	0.436

4.3 Modeling of Learning Effect Evaluation

4.3.1. Determination of input and output nodes

The determination of input nodes and output nodes is relatively simple, and their elemental composition can be judged by data. From the data point of view, the evaluation model not only needs to collect the data corresponding to the evaluation factors of the learners in the learning process before formal operation, but also needs to obtain the evaluation scores given by the experts to the learners as the training data, and then compare the data derived from the model with the actual data to complete the correction of the parameters within the model. If the data flow of this process is represented by a flowchart, the flow of data external to the evaluation model is shown in Figure 9, and a structure like "data input - model operation - feedback calculation" Such a structure represents the flow of data outside the entire evaluation model. According to the data direction of the evaluation model shown in the figure, it can be clearly seen that the nodes in the input layer are composed of evaluation factors of mobile scenario learning effect, which consists of four evaluation factors of learning effect, which are effectiveness, utility, guidance and economic value of learners in the process of mobile scenario learning. And there is only one output node, i.e. the learning effect score.

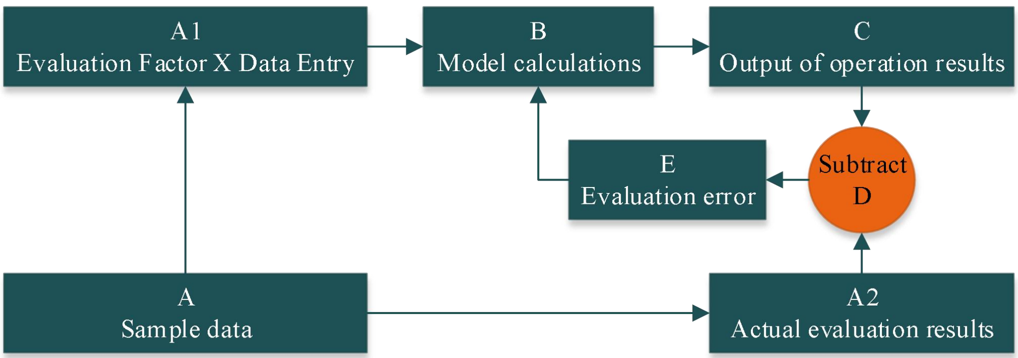


Figure 9. Evaluate the external data flow direction of the model.

4.3.2. Determination of the number of implicit layers and the number of nodes

For the evaluation of the learning effect of mobile situated learning, in which the evaluation factors are optimized with only four inputs, and the mapping of the relationship with the learning effect scores is relatively simple from the point of view of the information represented by the principal component factors, it is sufficient to choose a single implicit layer or a double implicit layer without choosing too many numbers of implicit layers to provide the computational efficiency of the model.Considering that there are fewer principal component factors in the evaluation model, the present paper chooses a single implicit layer structure. Although the number of hidden layers is determined, there is another hidden layer parameter to be determined in advance in the evaluation model of mobile scenario learning effect, i.e., the number of nodes in the hidden layer, however, the number of nodes in the hidden layer in the IGWO-CNN model is generally not a fixed reference, and it needs to be adjusted according to the data of the actual application, and the number of nodes of the intermediate hidden layer is set to 3 here.

After the determination of the input and output nodes and the selection of the relevant parameters of the hidden layer, the network topology of the whole evaluation model is basically determined, and the topology of the mobile situational learning evaluation model is shown in Fig. 10, and the whole network model is composed of a total of three layers of neurons, with the input neurons as the evaluation factors and the output neurons as the learning effect scores.

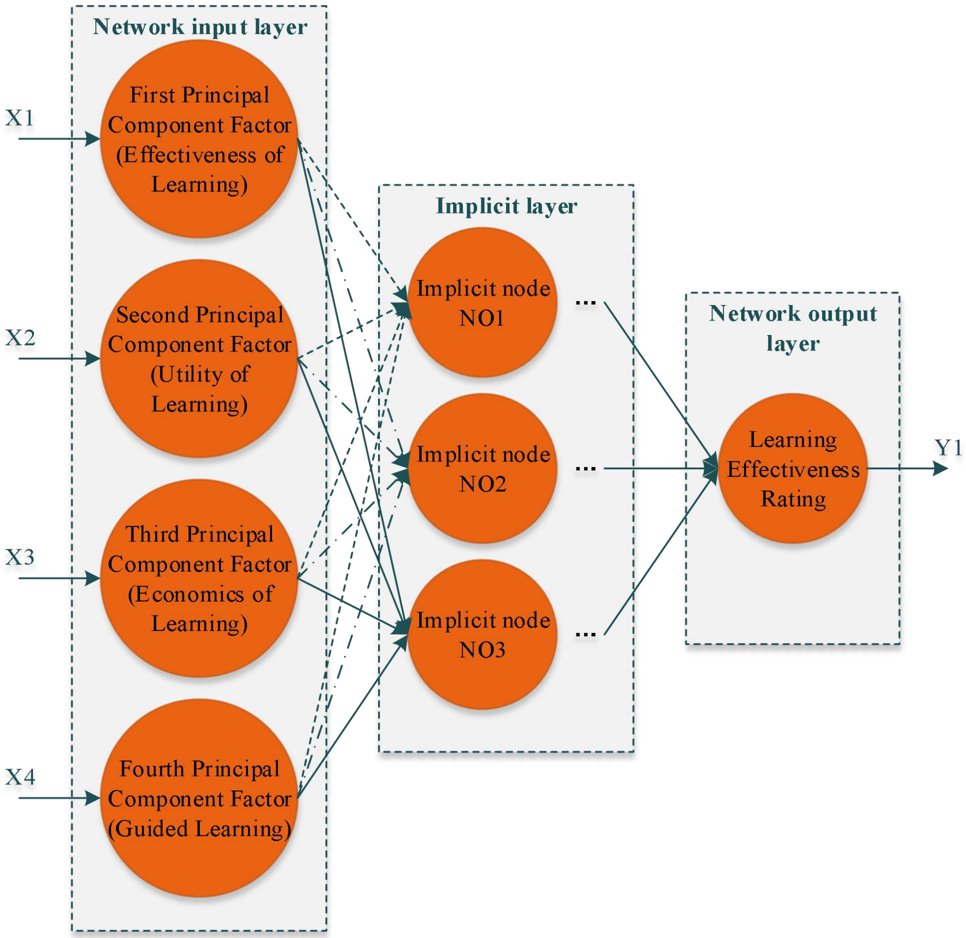


Figure 10. Topological structure of mobile scenario learning evaluation model.

4.3.3. Determination of other relevant parameters

In the running session of the model, the running parameters for evaluating the model mainly include the node weights, node thresholds and the action function. For the initial value selection of node weights and thresholds, the strategy is to select a random value between 0 and 1, which has achieved the effect of fast training. As can be seen from Chapter 2, in the design of the 3-layer BP neural network excitation function is generally used in the S-type excitation function, so this paper also selects the S-type function as the excitation function of the node.

5. Experimental results and discussion

5.1. Data sources

In order to test the effectiveness and superiority of the evaluation method proposed in this paper, the data collected from the quality evaluation of higher vocational English teachers from 2015 to 2024 were utilized in accordance with the evaluation index system of higher vocational English teaching quality constructed in this paper.

5.2. Analysis of results

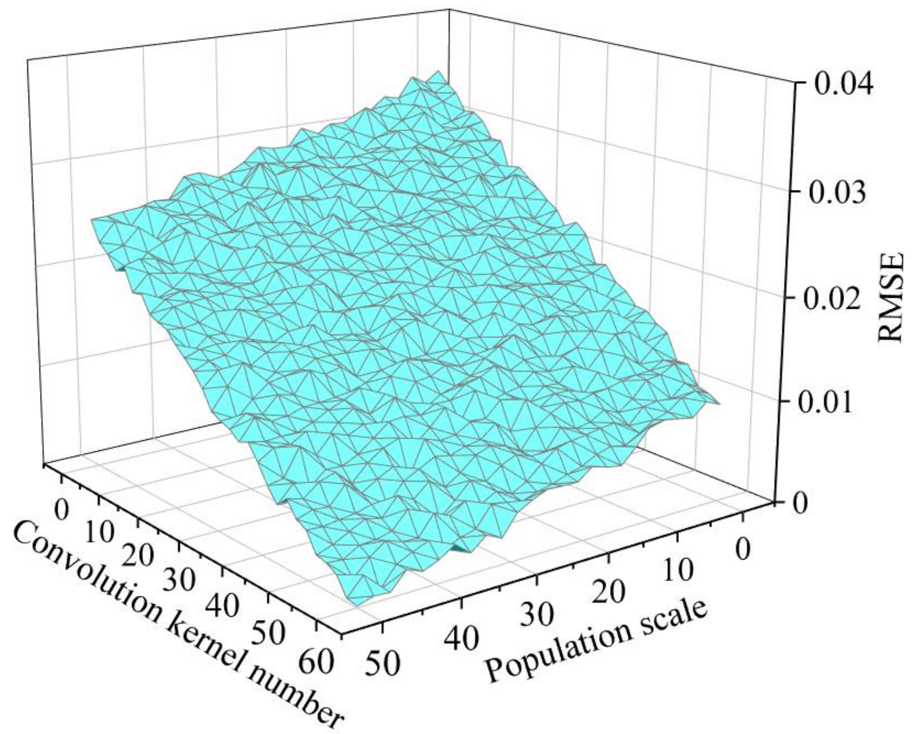
(1) Parameter setting.

In order to verify the accuracy and timeliness of the evaluation method of higher vocational English teaching quality based on the algorithm of this paper, five evaluation methods are selected for comparison, including BP, FOA-BP, KH-KELM, CNN, GA-CNN and IGWO-CNN.

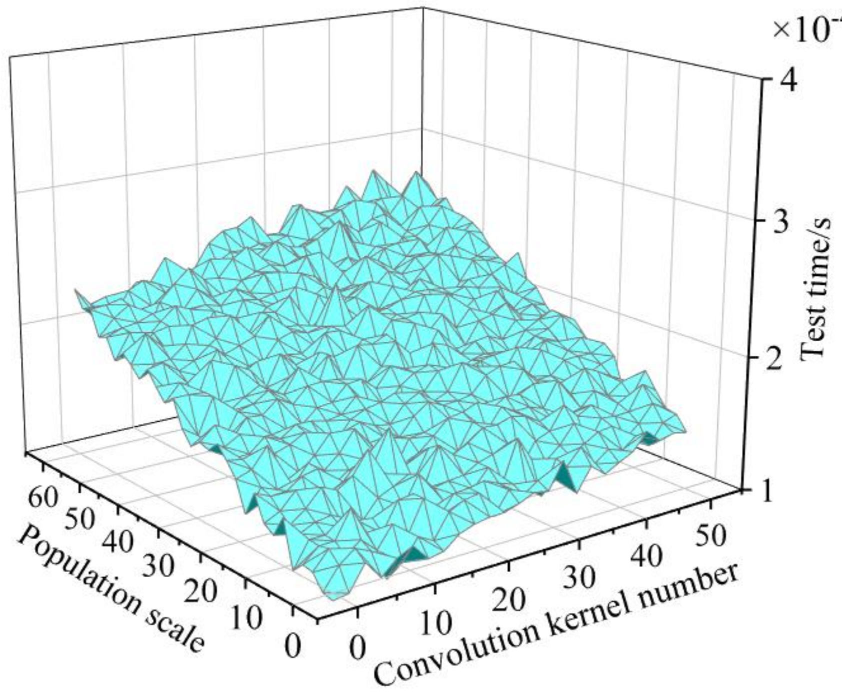
In order to investigate the influence of the population size of the algorithm and the number of CNN convolution kernels on the performance of the teaching quality evaluation model of higher vocational English in this paper, the evaluation data after dimensionality reduction is used to test the teaching quality evaluation model and to count the RMSE and evaluation time under different combination parameters. The results of the effects of different population sizes and convolution kernel numbers on the performance of the evaluation model are shown in Fig. 11 (Fig. a is the result of evaluation error and Fig. b is the result of testing time). From Fig. (a), it can be seen that the RMSE slightly tends to decrease with the increase of wolf population size and with the increase of the number of convolution kernels. From Fig. (b), it can be seen that the evaluation time of the test sample set after dimensionality reduction tends to increase slightly as the population size increases, and as the number of convolution kernels increases, the evaluation time of the test samples increases. In summary, the number of population size of this experimental species of this algorithm is taken as 30, and the number of CNN convolution kernels is taken as 20.

(2) Analysis of teaching quality evaluation results.

According to the above parameters, this subsection utilizes the test set to compare the performance of BP, FOA-BP, KH-KELM, CNN, GA-CNN, and the method of this paper.



(a) Evaluation error result



(b) Test time result

Figure 11. The influence of different population size and convolution number.

All the methods are evaluated using the data of the test set of the evaluation of the quality of higher vocational English teaching, and the mean square error change curve during the training of the model is shown in Figure 12. From the figure, it can be seen that the algorithm in this paper can effectively improve the evaluation performance of CNN network and avoid falling into the local optimum, and its mean square error is lower than that of other algorithms after 35 iterations, indicating that the algorithm in this paper can improve the evaluation accuracy of the model.

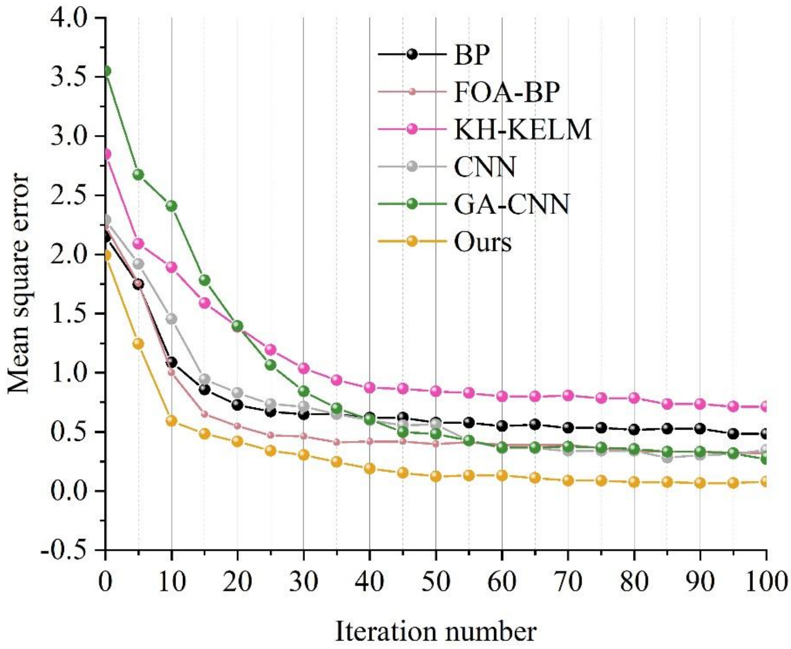
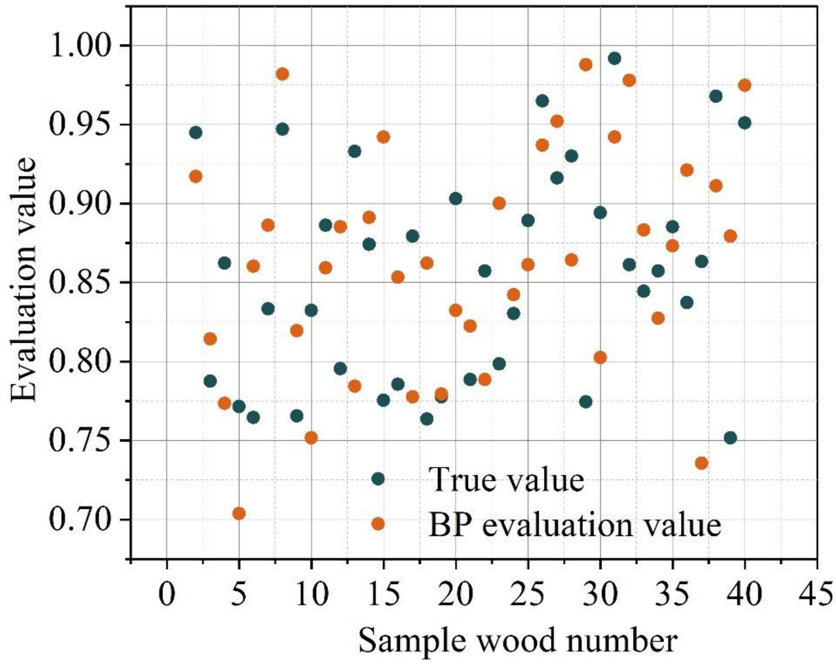
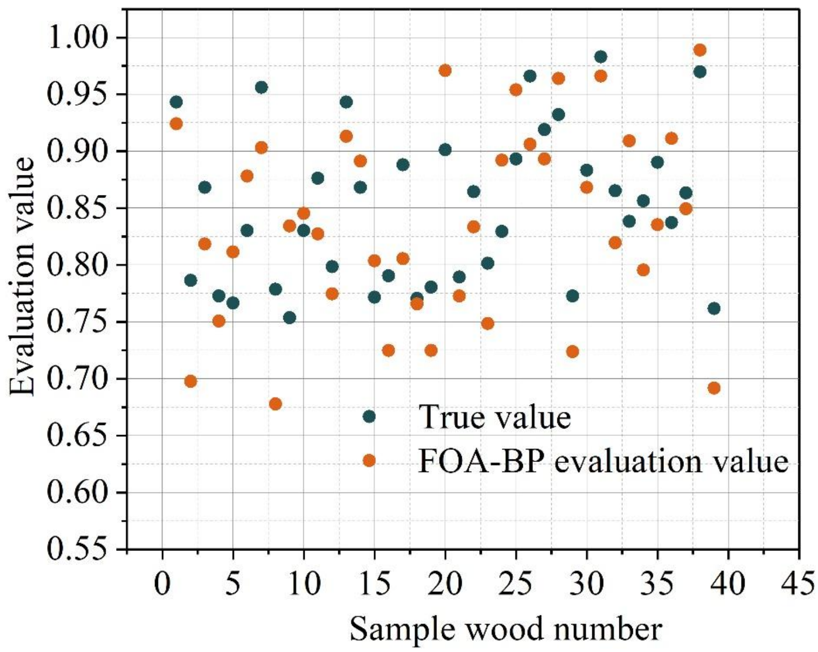


Figure 12. Mean square error curves of different model methods.

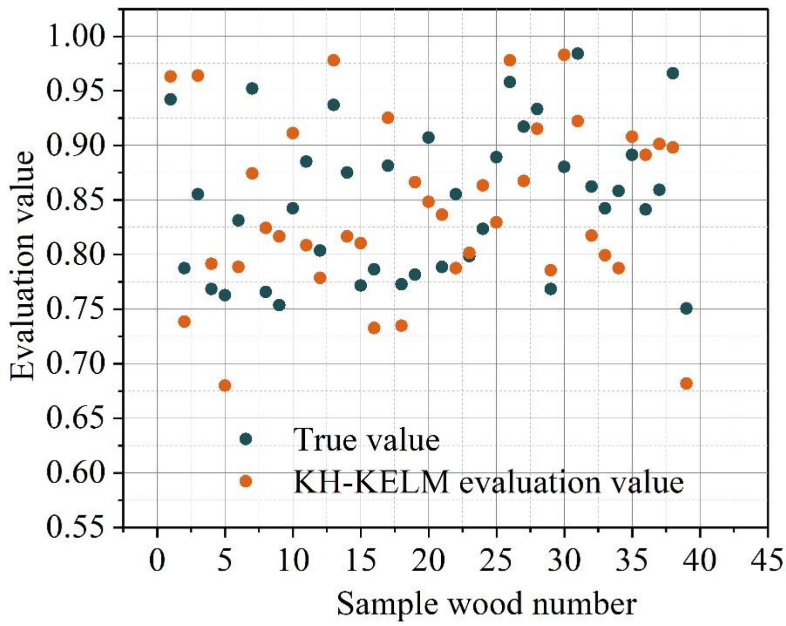
The evaluation results of the data of the test sample set of higher vocational English teaching quality indicators based on different algorithms are shown in Fig. 13 (Figs. a~f are BP, FOA-BP, KH-KELM, CNN, GA-CNN and this paper's algorithm, respectively). From the figure, it can be seen that the rating accuracy of optimized CNN neural network of this paper's algorithm is better than other algorithms. The statistical results show that the evaluation error of the higher vocational English teaching quality evaluation model of the optimized CNN network of this paper's algorithm is no more than 0.01 on the test set data, which is smaller than the evaluation error of other evaluation model methods, indicating that the model has a high approximation accuracy.



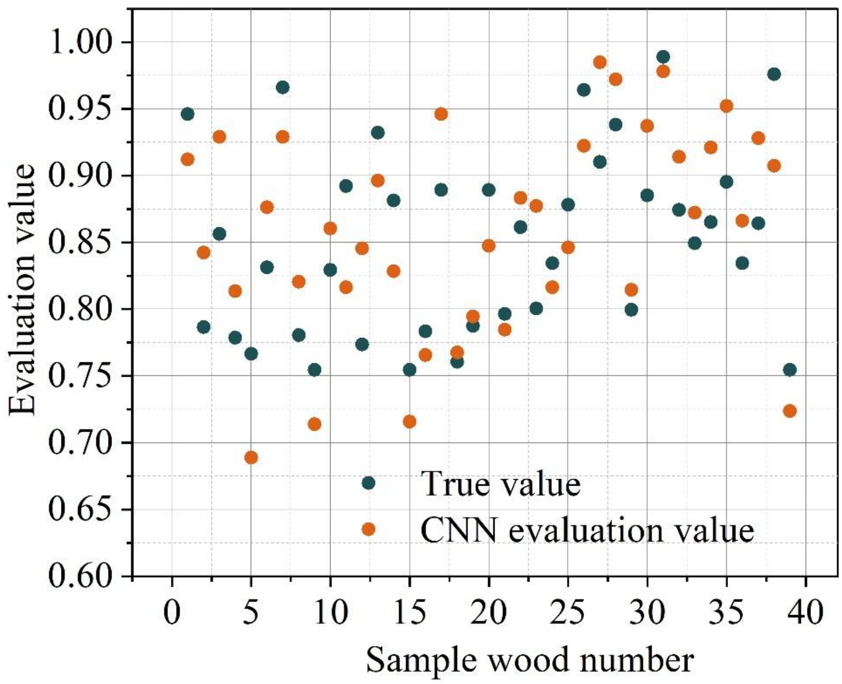
(a) BP



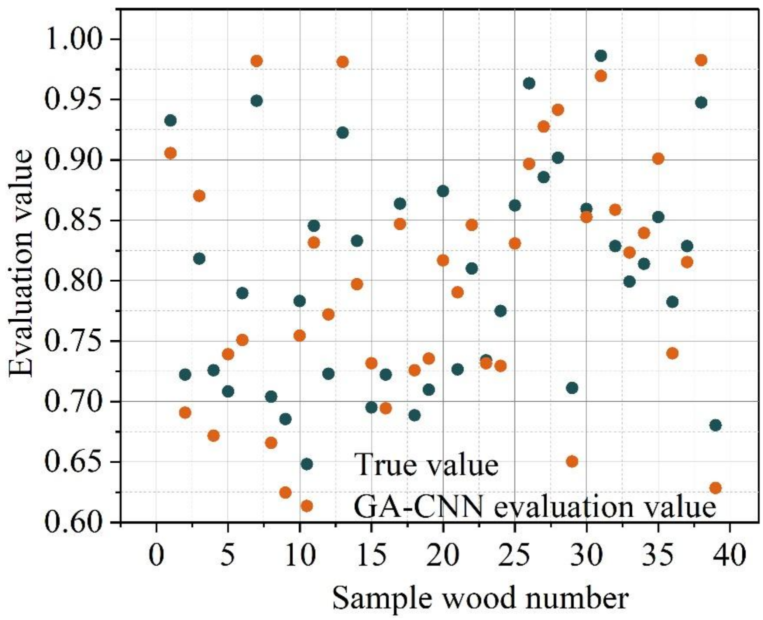
(b) FOA-BP



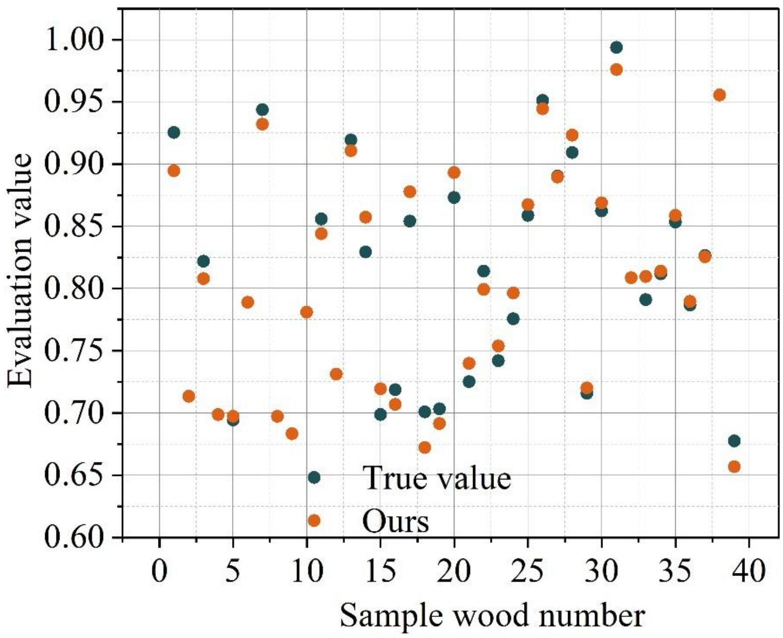
(c) KH-KELM



(d) CNN



(e) GA-CNN



(f) This algorithm

Figure 13. Test the evaluation results of samples using different model methods.

Comparison of algorithm performance metrics is shown in Table 5. The performance statistics include MAE, RMSE, MAPE, R-Squared, and evaluation time, and the statistics result in the mean and variance of 20 runs for each metric. As can be seen from the table, the MAE, RMSE, MAPE, R-Squared, and evaluation time of this paper's algorithm are superior both in terms of mean and standard deviation. In conclusion, this paper's algorithm has less evaluation error and its robustness is very good as well as robustness of evaluation time when compared with other algorithms.

Table 5. Comparison of algorithm performance indicators.

Algorithm	MAE		RMSE		MAPE		R-Squared		Time	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean/s	Standard deviation

BP	0.0429	4.63e-03	0.0549	4.12e-03	0.0015	1.08e-04	0.9309	6.63e-03	4.85e-02	1.85e-03
FOA-BP	0.0399	4.95e-03	0.047	4.36e-03	0.0011	1.26e-04	0.9554	6e-03	1.65e-02	1.62e-02
KH-KELM	0.053	4.35e-03	0.06	4.22e-03	0.0013	1.1e-04	0.9501	7.42e-03	4.52e-03	5.42e-04
CNN	0.0359	3.82e-03	0.0428	3.52e-03	0.0008	9.36e-05	0.9955	4.36e-03	3.65e-03	1.63e-03
GA-CNN	0.0244	1.85e-03	0.0252	1.76e-03	0.0006	4.75e-05	0.9644	1.42e-03	1.66e-04	1.35e-04
Ours	0.0092	9.33e-04	0.0107	8.96e-04	0.0001	2.23e-05	0.963	2.59e-04	1.25e-04	1.1e-04

6. Conclusion

This study proposes a personalized recommendation method for learning resources based on deep learning. By continuously learning the user's behavioral characteristics and constructing a deep learning model, the association between the user and the English teaching resources is effectively characterized, thus completing the recommendation of learning resources. At the same time, a learning effect prediction model based on IGWO-CNN is established, and intelligent algorithms are utilized to find the optimization of the machine learning parameters, and then the English learning effect prediction is tried. The experimental conclusions drawn from the article are as follows:

(1) In the experiments of the actual recommendation effect of the adaptive learning system, the algorithm of this paper not only has a response time of 4.5s under the test situation of 100 people, but also has a high success rate of 99.6%. Comprehensive experimental results can be concluded, this paper's algorithm in different training data conditions still has good stability, while the system can be constructed in this way to provide students with targeted test questions, in the actual management of student teaching has a high degree of practicality.

(2) From the evaluation results of different algorithms on the test sample set of higher vocational English teaching quality indicators, it can be concluded that the rating accuracy of the optimized CNN neural network of this paper's algorithm is better than that of other algorithms. The evaluation error of the test set data is no more than 0.01, which is smaller than the evaluation error of other evaluation modeling methods, thus it can be concluded that the model in this paper has the advantages of high precision and less time-consuming.

About the Author

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