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Retraction

Retracted: Intelligent Analysis and Application of Preschool Education Language Teaching Quality Based on Deep Neural Network

Journal of Sensors

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] H. Li and C. Niu, "Intelligent Analysis and Application of Preschool Education Language Teaching Quality Based on Deep Neural Network," *Journal of Sensors*, vol. 2022, Article ID 7548686, 11 pages, 2022.

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Research Article

Intelligent Analysis and Application of Preschool Education Language Teaching Quality Based on Deep Neural Network

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Language is the cornerstone of children's learning knowledge and exploring the world. Language teaching is an indispensable part of early childhood education, which can help children improve their communication ability and help children communicate with classmates and teachers in school. The teaching form of preschool language education is too single, which does not conform to children's own learning ability. Therefore, in teaching, teachers should actively optimize the language environment to make children willing to express themselves in language: introducing game activities to make children want to express themselves in language. With the help of situational display, children like to express themselves in language and carry out performance activities to give children the opportunity to express themselves in language. With the help of home force, children dare to express themselves in language. Children are in a dynamic stage of rapid growth. In order to enable children to learn language effectively, teachers should make clear the development center of children and their mastery of language. To guide language teaching in accordance with students' aptitude for a long time, at the same time, we should update our rigid views on children at any time, boldly innovate the content and thinking mode of children's language teaching activities, and mobilize children's initiative and enthusiasm to participate in language learning, so that they can achieve the language learning goals of being able to speak, loving to speak and bravely speaking. This paper selects the learning situation of preschool children as the object, establishes an evaluation model by using the hybrid GA-BP neural network method, and makes an empirical analysis on the development of preschool education in Liaoning Province. The GA-BP neural network model is trained by MATLAB 7.0, and the simulation results show that the model can evaluate the development of preschool education scientifically, and it is scientific and practical. According to the results of this paper, the corresponding evaluation model of preschool education language teaching quality is put forward, which makes a good prediction preparation for children to learn language better in advance.

1. Introduction

3-6 years old is the golden age of children's language learning and development. The relevant outline clearly points out: "The key to developing preschool education language is to create an environment in which they want to speak, dare to speak, like to speak, have the opportunity to speak and get positive responses." Literature [1] expounds the scientific evaluation of the development of preschool education based on the BP neural network algorithm. Literature [2] examines the two dimensions of family language policy—language ideology and language practice—and the relationship between family language policy and the development of children's narrative macrostructure and discusses the key factors to realize the sustainable development of early language education. Literature [3] is aimed at dealing with and discussing the dialogue between critical teaching method and language education in the context of English as a global lingua franca. Literature [4] explores literacy practices in adult intermediate second language teaching, involving two teachers and their different student groups who undertook a four-week literary work. Literature [5] expounds the comparison of educational language policies in subjective language, minority language, and foreign language education between China and Australia. Literature [6] studied the language outcomes of 174 young children in the Bucharest Early Intervention Program, the first randomized trial of foster placement after institutional care. The purpose of literature [7] is to evaluate the content of vocabulary game application to children's language learning. Literature [8] shows a model of higher education quality evaluation and decision-making based on BP neural network and analytic hierarchy process. Literature [9] predicts the success or failure of education population based on the convolution neural network method. Reference [10] proposes a new penalty estimation method for sparse DNN, which solves the problems existing in sparse constraints. Literature [11] proposes a method based on the deep neural network for nonparametric regression of functional data. Reference [12] gives the numerical results of the sparse data problem of tomography. NETT has good performance even for different types of unknowns in training data. A new hybrid forecasting system CFML (complementary set empirical mode decomposition- (CEEMD-) fuzzy time series- (FTS-) multiobjective gray wolf optimizer- (MOGWO-) long-term and short-term memory (LSTM)) is proposed and tested in reference [13]. Literature [14] uses a new multivariate time series convolution network (M-TCN) model to analyze Beijing PM2.5 and ISO-NE data sets. Literature [15] expounds preschool teachers' understanding and needs for children's language education and focuses on the purpose, content, method, evaluation, and required facts of children's language education. Literature [16] studies the problems existing in the development of preschool education, the continuous reform aimed at solving these problems, and the importance of the "first step" of the national plan. Literature [17] is aimed at seeking the application direction of new media in preschool education, so as to promote the better development of preschool education under the background of new media era. Literature [18] expounds that the success of preschool education in Japan is closely related to Japan's economic development level and Japan's emphasis on education. Literature [19] expounds the practice and exploration of preschool education art curriculum reform under the new situation, hoping to provide reference for relevant personnel. Literature [20] designs an intelligent inventory forecasting system based on deep network technology. Based on stock financial indicators and stock changing trends, it studies the quantitative stock selection problem with multiple influencing factors and proposes a stock trend identification algorithm to build a stock selection model. Reference [21] uses a deep neural network to determine one-dimensional fast ion velocity distribution function from ion cyclotron emission data. Reference [22] uses neural networks to process phase-time measurement information. The novelty of the proposed method lies in the selection of classification attributes and the binary classification of perceptron algorithm. Reference [23] is aimed at applying ANN to predict the bulk density of composite aggregates, i.e. coarse, medium, and fine aggregates. In reference, the prediction model constructed by the BP neural network can provide a basis for corrosion control in refineries. Reference [24] describes the application of the neural network in nonlinear electronic equipment: building Volterra series model.

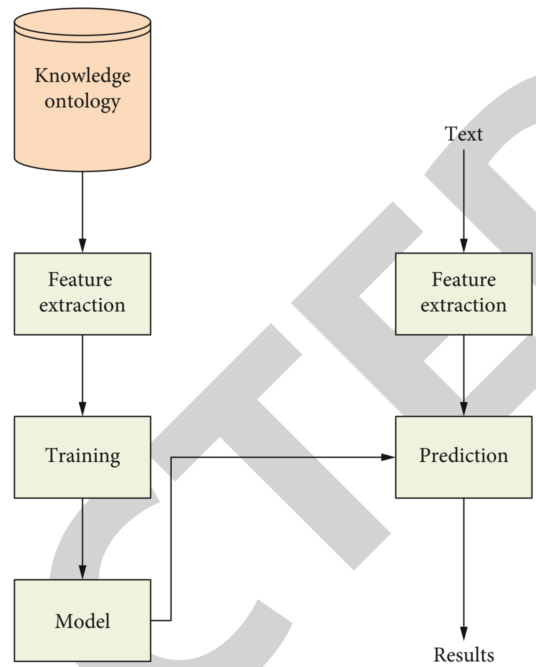

Figure 1: Language map construction.

2. Intelligent Language Teaching

An intelligent tutoring system (ITS) is a classroom teaching system widely used in the field of education. It interacts with children through intelligent teaching methods and means to help children learn language quickly and effectively. Since the last century, the intelligent tutoring system has not only achieved rapid development, resulting in the emergence of many intelligent tutoring websites and educational platforms, but also promote the development of the intelligent tutoring system. One of the core issues of the intelligent tutoring system is the acquisition and effective utilization of knowledge. In spite of the progress in this field, the acquisition and effective use of knowledge is still a prominent problem in the intelligent teaching system. Specifically, on the one hand, knowledge is still very limited and difficult to update. Most of the existing knowledge sets of the intelligent tutoring systems are still constructed at one time, and knowledge is obtained from limited data sets. Faced with the rapid growth of information, the limited knowledge set has been difficult to meet the needs of learners for knowledge acquisition. On the other hand, the traditional teaching mode is adopted, and today's children's thinking is very jumping, so it is necessary to analyze and integrate new thinking with existing thinking modes to reduce conflict rules. Its complex teaching process makes language learning a challenge.

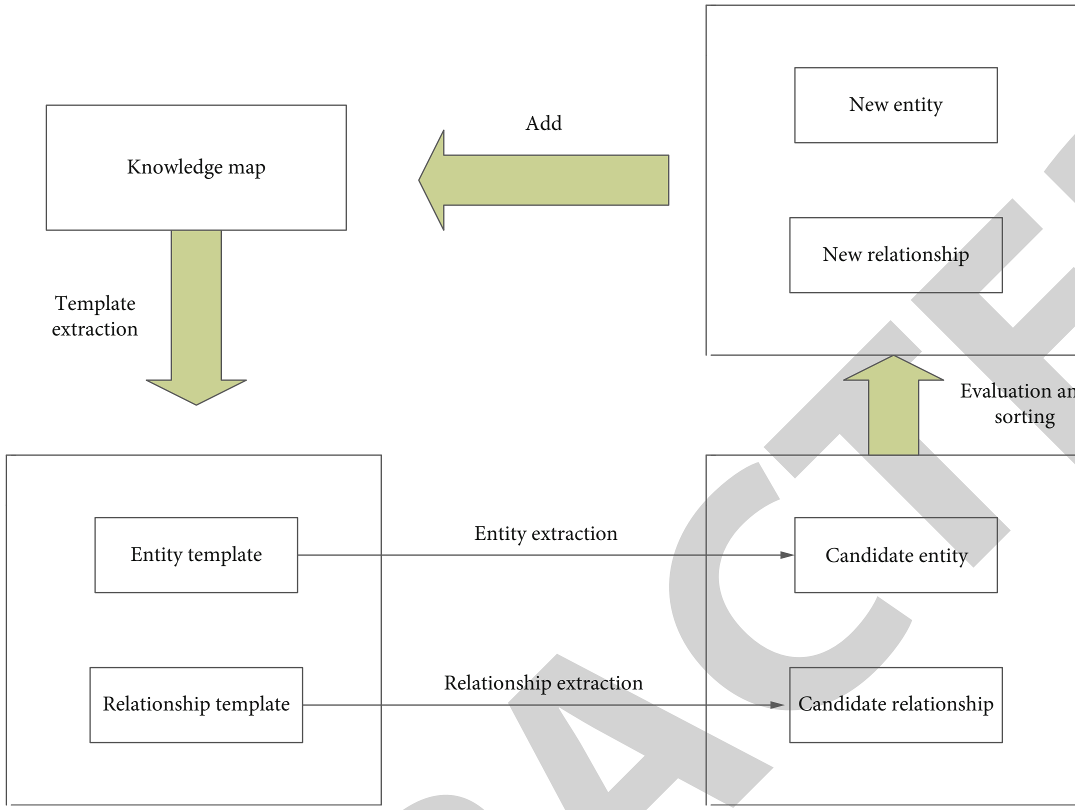

FIGURE 2: Extension of the knowledge map.

2.1. Meaning of Language Teaching Activities in Preschool Education. A kindergarten language teaching activity is a kind of collective growth activity, that is, to organize all children to learn language with others purposefully, organized, and planned, so that children can join in and improve their listening and expressing ability. In the effective accumulation and emotional development, we can get the development of cognitive things and correct behaviors and then help the improvement of language use ability. The development of language is inseparable from the development of children's thinking. Therefore, kindergarten language teaching activities can not only guide children to correctly master language as a social "tool" but also expand children's thinking through planned and purposeful language education, so that they can accumulate language experience and develop emotional behavior in the process of listening, expressing and reading. At the same time, language also plays an important role in children's cognitive development. It can help children intuitively understand things and learn knowledge and explore the world with curiosity. It is an indispensable cornerstone for children's growth and learning in all aspects. Children's language ability is an important prerequisite in his growth process, and the process of learning language is also a process of developing thinking. Children are taught how to learn language and how to use language correctly, and their intelligence is also developed accordingly. It can be seen that language education is a necessary way to help children grow up in an all-round way.

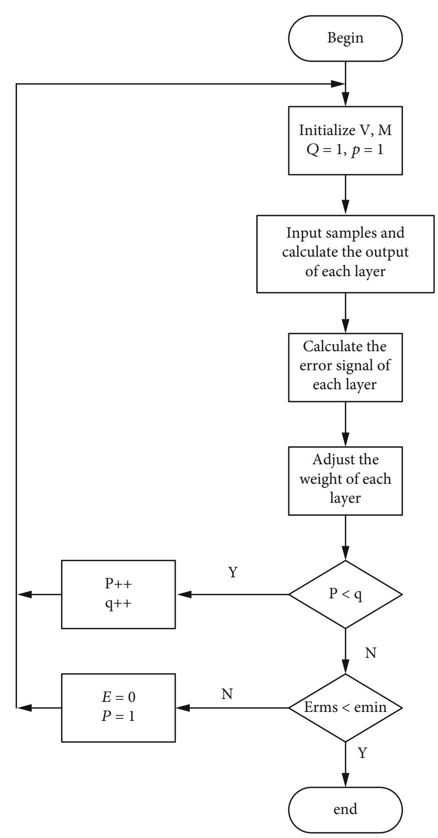

FIGURE 3: Step diagram.

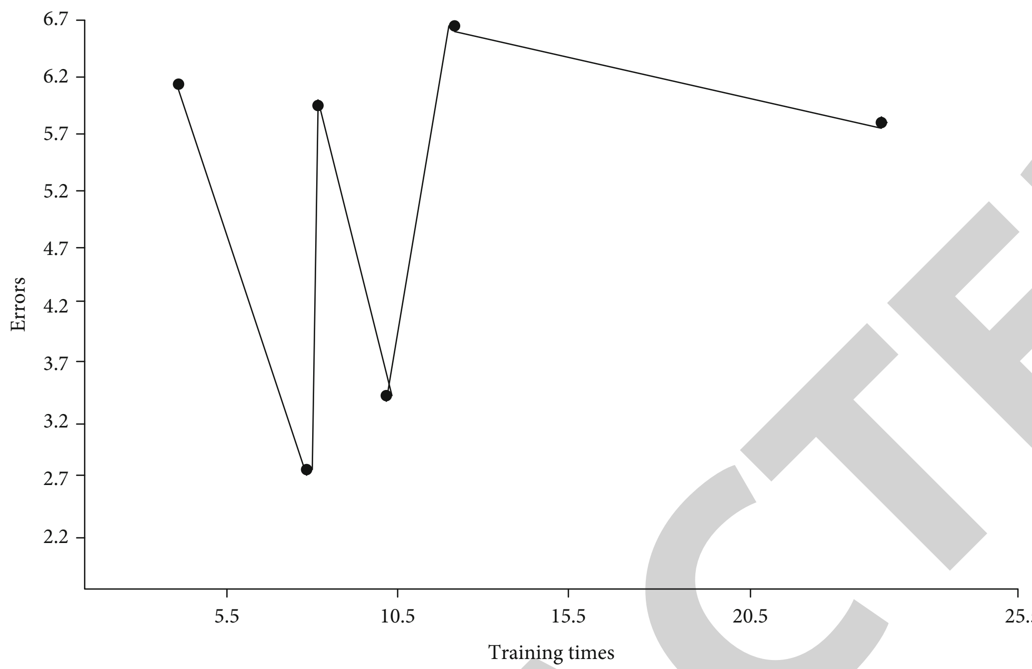

Figure 4: Simulation experiment.

2.2. Construction of Language Knowledge Map. The construction of the core knowledge map is an indispensable link in the construction of core map, and its purpose is to establish a relatively accurate knowledge set of entities and entity relations, so as to provide a good foundation for the expansion of knowledge map. We can use Chinese teaching ontology knowledge base to establish core knowledge map. An automatic identification method of entity association. This method can be regarded as a classification process, that is, judging that two entities belong to a certain relationship. Firstly, the domain experts give the basic set of entity relations and mark some entity relations. Then, the classification model is trained by using the above training data. In the prediction stage, after extracting the features from the text, the trained model predicts according to these features and confirms the relationship between entities through manual inspection. The process is shown in Figure 1.

2.3. Knowledge Map Expansion. The core knowledge map is the main body that provides accurate domain knowledge, but the number of entities is small and the capacity is limited, which does not have corresponding practical significance, so it is necessary to further expand the domain of the knowledge map. We can extract domain knowledge from the open network encyclopedia knowledge base. Encyclopedia knowledge corpus belongs to open knowledge text data on the Internet. It has the characteristics of large scale and continuous renewal and expansion. The main sources of Chinese encyclopedia knowledge corpus are Chinese Wikipedia and Baidu Encyclopedia. This kind of knowledge base is rich in entities and entity relationships, which can not only supplement a large number of entities and relationships but also examine the relationships between entities in the existing core knowledge map to supplement new relationships. On the other hand, entity and entity relationship extraction often needs enough training data. However, the number of entities in the core knowledge map is limited, so it is difficult to obtain ideal recognition performance by supervised learning method. To this end, this paper proposes a model of entities moving with each other, as shown in Figure 2.

Table 1: Comparison of results.

Sample number	Actual results	Simulation results	Errors	Relative errors
1	97.3	92.5	5.28	0.07
2	90.5	87.1	4.34	0.06
3	91.2	86.2	4.42	0.06
4	89.8	81.4	6.17	0.07
5	88.7	82.5	3.62	0.03
6	93.4	86.2	5.63	0.05
7	90.0	79.1	8.21	0.08
8	90.6	79.9	8.17	0.08
9	96.1	85.9	6.12	0.07
10	94.2	81.3	7.21	0.07
11	86.9	76.8	8.43	0.08
12	88.3	79.4	7.48	0.08
13	81.5	68.9	8.43	0.09
14	91.2	81.2	8.45	0.09
15	83.7	73.8	8.31	0.09

Table 2: Comparison of algorithms.

Algorithm	Training steps	Convergence accuracy
Gradient descent method	2000	0.000615
Adaptive learning rate gradient descent method	2000	0.00750
BL neural network algorithm for integrated wiring system	10	0.0851
RBF neural network algorithm	300	0.4532
Pacific application algorithm	30	0.2711
Proportional conjugate gradient algorithm	30	0.3421

Table 3: Experimental data of the gradient descent method.

	Accuracy	Recall	F1	AUC
Sample1	0.675	0.575	0.555	0.621
Sample2	0.643	0.591	0.679	0.592
Sample3	0.667	0.569	0.621	0.583
Sample4	0.698	0.588	0.541	0.557
Sample5	0.681	0.576	0.662	0.632

3. Teaching Evaluation Design of Preschool Education Neural Network

3.1. BP Neural Network Algorithm. The mathematical formulas involved in the training process of the BP neural network in preschool education language teaching are as follows:

$$x_i = \frac{x_{\max} - x_i}{x_{\max} - x_{\min}}. \tag{1}$$

Connection weights of nerve cells in hidden layer:

$$hi(k) = \sum_{i=1}^{n} w_{ih} x_i(k) - b_h. \tag{2}$$

The error E between the network output and the expected output is as follows:

$$E = \frac{1}{2}(d-0)^2 = \frac{1}{2}\sum_{k=1}^{1}(d_k - o_k)^2. \tag{3}$$

Output function is as follows:

$$f(x) = \frac{1}{1+e^{-x}} \tag{4}$$

Activation function is as follows:

$$f(x) = \frac{1}{a + be^{-Cx}}. \tag{5}$$

The formula of error E in hidden layer is as follows:

$$E = \frac{1}{2}\sum_{K=1}^{1}\left\{d_k - f\left[\sum_{j=0}^{m} f\left(\sum_{j=0}^{m} w_{jk} y_j\right)\right]\right\}^2. \tag{6}$$

Error E is expanded to the output layer by the following formula:

$$E = \frac{1}{2}\sum_{K=1}^{1}\left\{d_k - f\left[\sum_{j=0}^{m} w_{jk} f\left(\sum_{i=0}^{n} v_{ij} x_i\right)\right]\right\}^2. \tag{7}$$

Using the gradient descent method, the weights are continuously adjusted as follows. The formula is as follows:

$$\begin{aligned} \Delta w_{jk} &= -\eta \frac{\vartheta E}{\vartheta w_{jk}} \; (j = 0, 1, \cdots, m\,; k = 1, 2, \cdots, l), \\ \Delta v_{jk} &= -\eta \frac{\vartheta E}{\vartheta v_{jk}} \; (i = 0, 1, \cdots, n\,; k = 1, 2, \cdots, m). \end{aligned} \tag{8}$$

After continuous cycle, the value adjustment function of BP learning algorithm weight is

$$\begin{aligned} \Delta w_{jk} &= \eta \delta_k^0 y_j = \eta (d_k - o_k) o_k (1 - o_k) y_j, \\ \Delta v_{jk} &= \eta \delta_j^y x_i = \eta \left(\sum_{k=1}^{1} \sigma_k^0 w_{jk}\right) y_j \left(1 - y_j\right) x_i. \end{aligned} \tag{9}$$

Update BP parameters:

$$E_j^i = 0.5 * \left(T_j^i - yo_j^i\right),$$

$$\delta_j^{(2)}(k) = \left(T_j^k - yo_j^p\right) * yo_j^p * \left(1 - yo_j^p\right),$$

$$\delta_j^{(1)}(k) = \sum_{i=1}^{m}\left[w_{ij}^{(2)} * \delta_j^{(2)}(k)\right] * yi_j^k * \left(1 - yi_j^k\right),$$

$$E = \frac{\left(\sum_{i=1}^{k} E_i\right)}{k},$$

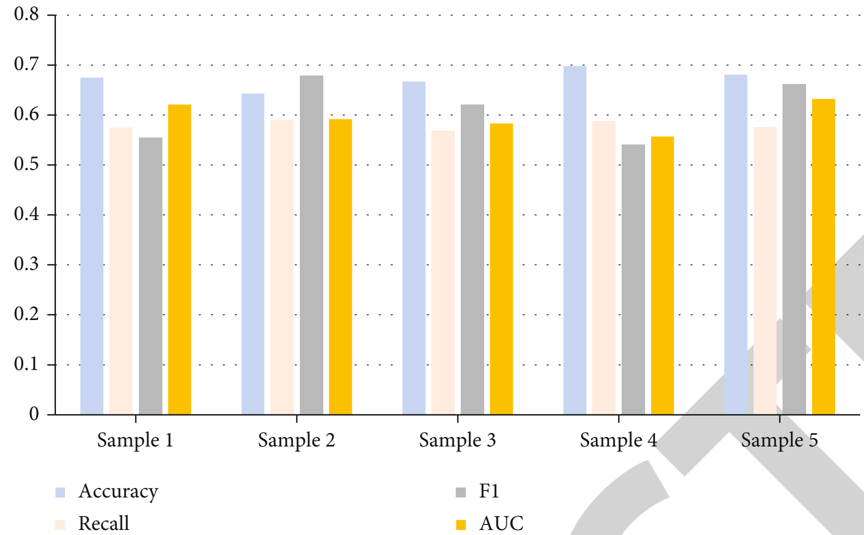

Figure 5: Index comparison chart of the gradient descent method.

Table 4: Experimental data of the adaptive learning rate gradient descent method.

	Accuracy	Recall	F1	AUC
Sample1	0.725	0.625	0.655	0.721
Sample2	0.713	0.631	0.699	0.692
Sample3	0.727	0.663	0.721	0.683
Sample4	0.718	0.668	0.741	0.757
Sample5	0.691	0.686	0.682	0.732

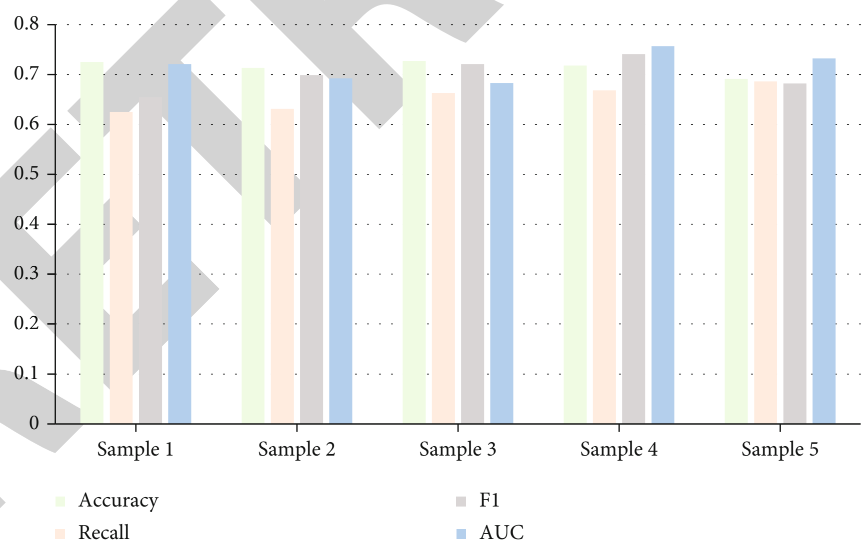

Figure 6: Index comparison chart of adaptive learning rate gradient descent method.

$$w_{ij}^{(2)} = w_{ij}^{(2)} + \eta * \sum_{i=1}^{k} \left[\delta_j^{(2)}(l) * yo_i^l \right],$$

$$w_{ij}^{(1)} = w_{ij}^{(1)} + \eta * \sum_{i=1}^{k} \left[\delta_j^{(1)}(l) * x_i^l \right]. \tag{10}$$

3.2. RBF Neural Network. The mathematical formulas involved in the training process of the RBF neural network are as follows:

Radial basis function:

$$y(x) = \sum_{i=1}^{N} w_i \varnothing(\|x - c_i\|). \tag{11}$$

Table 5: Experimental data.

	Accuracy	Recall	$F1$	AUC
Sample1	0.825	0.825	0.855	0.821
Sample2	0.813	0.831	0.899	0.892
Sample3	0.827	0.863	0.821	0.883
Sample4	0.818	0.868	0.841	0.857
Sample5	0.891	0.886	0.882	0.832

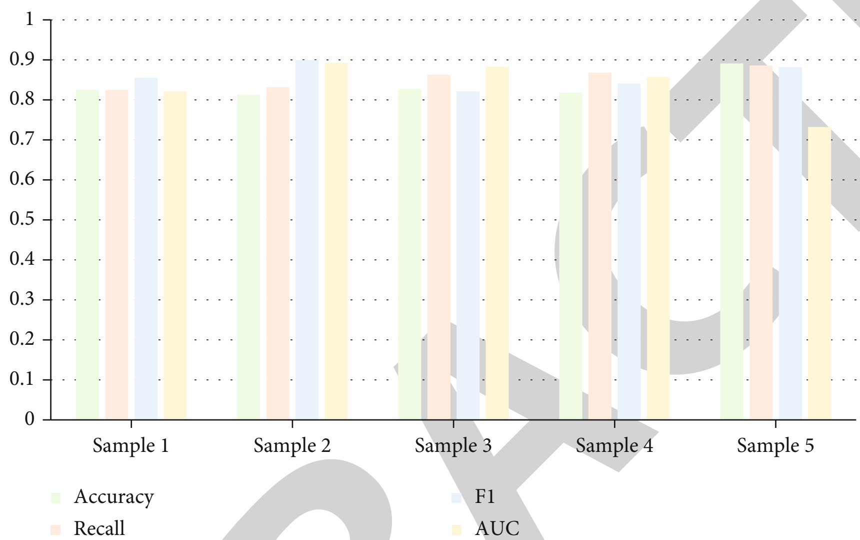

Figure 7: Comparison chart of the GA-BP neural network algorithm indexes.

Table 6: Experimental data.

	Accuracy	Recall	$F1$	AUC
Sample1	0.725	0.725	0.655	0.721
Sample2	0.713	0.731	0.699	0.692
Sample3	0.727	0.663	0.721	0.683
Sample4	0.718	0.668	0.741	0.657
Sample5	0.691	0.686	0.682	0.632

The result of this approximation function $y(x)$ can be regarded as the sum of many radial basis functions, each of which is associated with a different center $c_i$and weighted by an appropriate number w_i.

Calculate variance:

$$\sigma = \frac{d_{\max}}{K}. \tag{12}$$

Calculate $\widehat{y}_i(n)$ from $x(n)$:

$$\widehat{y}_i(n) = \sum_{k=1}^{M} W_K \varnothing[x(n), C_K, \sigma_K]. \tag{13}$$

Update RBF parameters:

$$W(n+1) = W(n) + \mu_w e(n) \varnothing(n),$$

$$\begin{aligned} C_K(n+1) &= C_K(n) + \mu_c \frac{e(n) W_K(n)}{\sigma_k^2(n)}, \\ &\varnothing[x(n), C_K(n), \sigma_K][x(n) - C_K(n)], \end{aligned}$$

$$\begin{aligned} \sigma_K(n+1) &= \sigma_K(n) + \mu_\sigma \frac{e(n) W_K(n)}{\sigma_k^2(n)}, \\ &\varnothing[x(n), C_K(n), \sigma_K][x(n) - C_K(n)]^2, \end{aligned}$$

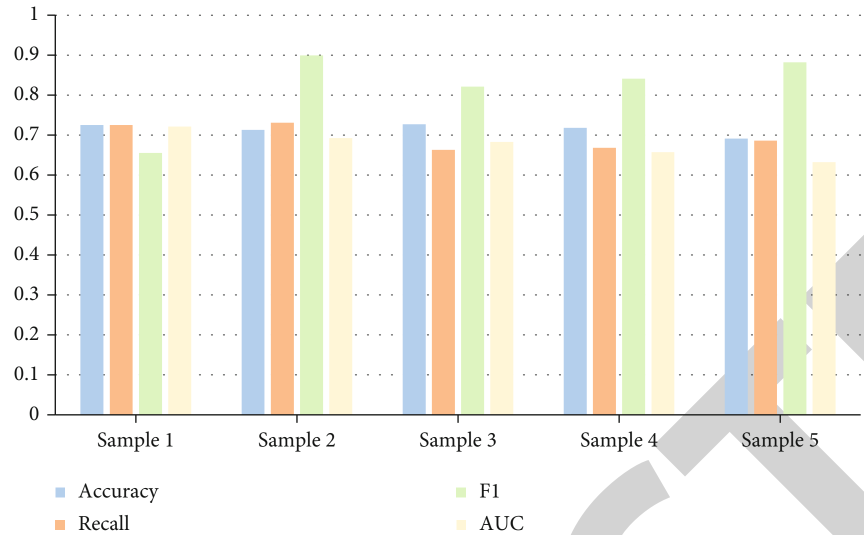

FIGURE 8: Comparison chart of the RBF neural network algorithm indexes.

TABLE 7: Experimental data.

	Accuracy	Recall	$F1$	AUC
Sample1	0.775	0.765	0.655	0.724
Sample2	0.773	0.761	0.659	0.694
Sample3	0.777	0.663	0.751	0.684
Sample4	0.778	0.668	0.751	0.654
Sample5	0.671	0.666	0.652	0.634

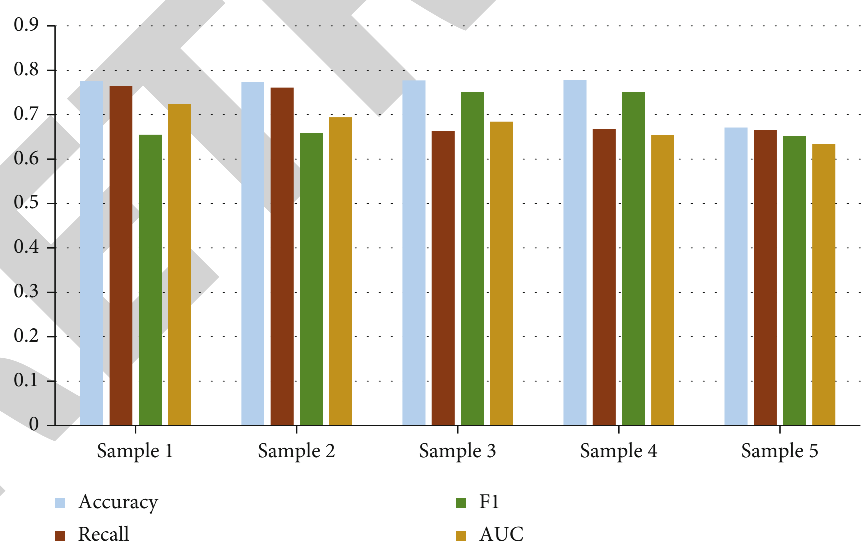

FIGURE 9: Comparison chart of PSO algorithm indexes.

$$\varnothing(n) = \begin{cases} \varnothing[x(n), c_1(n), \sigma_1], \varnothing[x(n), c_2(n), \sigma_2], \\ \cdots, \varnothing[x(n), c_N(n), \sigma_N], \end{cases}$$

$$e(n) = \hat{y}_i(n) - y_d(n). \tag{14}$$

$y_d(n)$ is the failure output, and μ_c, μ_σ, $\sigma_N$are the mapping of three parameters.

4. Experiment

For the evaluation of teaching quality, the algorithm programming steps of the BP neural network of the student evaluation system are shown in Figure 3.

4.1. Simulation Experiment. We evaluate the teaching quality of preschool education language education, set the number of hidden layer neurons as 7, and determine 7 as the number of hidden layer neurons. The experimental data are shown in Figure 4.

Using the hybrid GA-BP neural network algorithm to the preschool education language teaching quality evaluation simulation experiment, it predicts the evaluation results of 15 groups of sample data and compares the simulation evaluation results with the actual evaluation results as shown in Table 1.

4.2. Model Comparison. Comparing different functions with different convergence accuracy and training steps, from the table and experimental data, GA-BP is the most suitable training function in this paper. Data are shown in Table 2.

Five samples are selected to test the performance index of language teaching quality for all the algorithm models in the above table, and the accuracy rate, recall rate, $F1$ value, and AUC value are compared, respectively. The experimental data are as follows.

Using the gradient descent method, the performance index of the teaching quality analysis model of preschool language education is tested. The experimental data are shown in Table 3.

According to the data in the above table, it is counted into a bar chart, as shown in Figure 5.

Test the performance index of the teaching quality analysis model of preschool language education by an adaptive learning rate gradient descent method. The experimental data are shown in Table 4.

According to the data in the above table, it is counted into a bar chart, as shown in Figure 6.

We test the GA-BP neural network algorithm for preschool language education teaching quality analysis model to achieve what level of performance indicators, and data are shown in Table 5.

According to the data in the above table, it is counted into a bar chart, as shown in Figure 7.

We test the performance index level of RBF algorithm on the teaching quality analysis model of preschool language education. The experimental data are shown in Table 6.

According to the data in the above table, it is counted into a bar chart, as shown in Figure 8.

We test the performance index of the PSO algorithm on the teaching quality analysis model of preschool language education. The data are shown in Table 7.

According to the data in the above table, it is counted into a bar chart, as shown in Figure 9.

4.3. Contrast Experiment. According to the abovementioned comparison chart of preschool education language teaching quality index test, through the model index data results of the chart, the hybrid neural network algorithm and RBF neural network algorithm are more practical for other models. We test and compare the language learning effects of these two models on children, as shown in Figures 10 and 11:

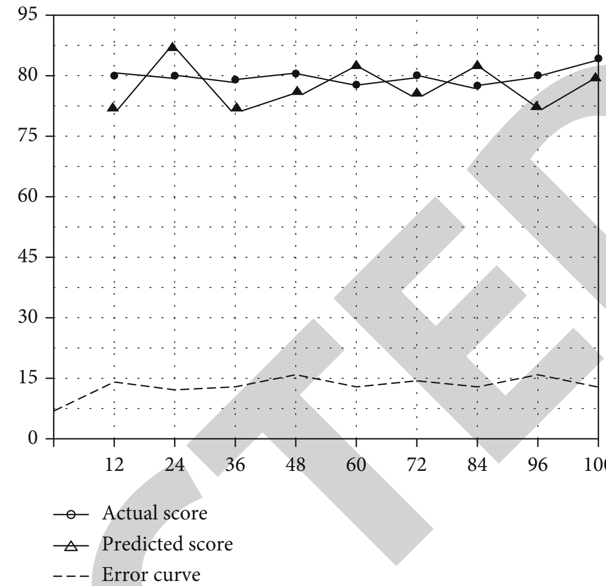

Figure 10: Learning renderings.

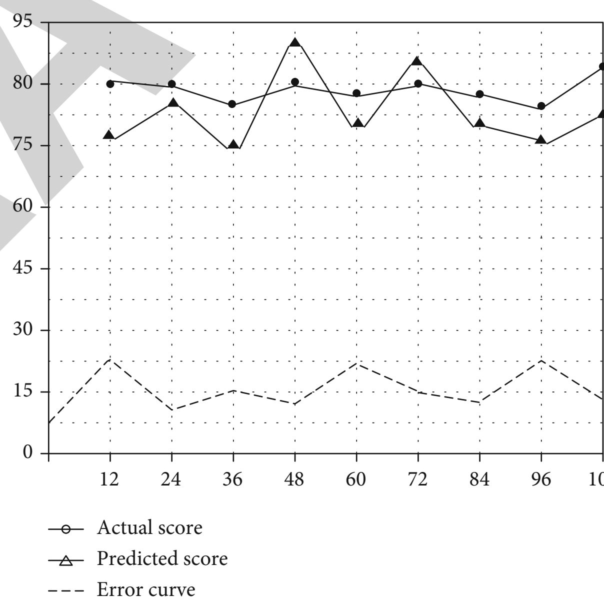

Figure 11: Learning renderings.

According to the comparison chart of the two algorithms, the error curve of the hybrid neural network algorithm is relatively flat, so it is more practical for the evaluation of teaching quality.

5. Conclusion

Teaching evaluation is regarded as an effective method to test teaching quality in colleges and universities. Through the observation and assessment of teachers' teaching in a working period, scientific and effective assessment results are formed, and the teaching process is constantly improved according to the assessment results. This paper is mainly based on the intelligent analysis and application of language teaching quality in preschool education based on the deep neural network. The research results are as follows:

(1) Comparing the convergence accuracy and training steps of these algorithms in this paper, the hybrid GA-BP neural network algorithm has fast evaluation speed and high accuracy

(2) The results show that the hybrid GA-BP neural network algorithm and RBF algorithm are more suitable for preschool language teaching

(3) For the analysis of language teaching quality in preschool education, we can clearly see that the error of the hybrid GA-BP neural network algorithm is smaller and more stable in the children's learning effect diagram after comparative experiment

(4) For children in preschool education, we should provide new ideas and methods to guide children's teaching, which also plays a certain role in improving teaching quality

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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