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Research Article

Research on the Evaluation Algorithm of English Viewing, Listening, and Speaking Teaching Effect Based on DA-BP Neural Network

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Improving the teaching of viewing, listening, and speaking courses is the key to produce better workers for society. Improving teaching quality is therefore a key teaching objective. One way to improve the quality of English instruction is to conduct a scientific evaluation of videos, audios, and spoken language instructions. This paper investigates the neural network model and the evaluation of teaching effect in depth in order to solve the complex nonlinear problem of evaluating the impact of English viewing, listening, and speaking. The DA-BP neural network model is proposed as a result of the existing research's shortcomings. The BP neural network is basically an algorithm which is multilayered feed-forward network that is trained actually to the error back propagation algorithm. The accuracy of the BP neural network's evaluation is influenced by its parameter selection in this paper, and the dragonfly algorithm (DA) is used to optimize the BP model's initial connection weight and threshold parameters. According to the research results, DA-BP improves the accuracy of evaluating the viewing, listening, and speaking classroom teaching quality in college English and offers a new approach for evaluating the audio-visual classroom teaching effect in college English.

1. Introduction

Everyday communication and expression rely heavily on fluency in English listening and speaking, so these skills are critical for fluency in the language. Consequently, a large number of undergraduate and graduate institutions now offer separate hearing and speaking courses, as well as seeing, listening, and speaking courses, in addition to reading and writing. Viewing, hearing, and speaking are all part of the training, and the goal is to enhance application skills in English. Create a realistic language environment for pupils using modern technology such as projectors. This will allow students to comprehend English material in all directions. While this is going on, a wide range of topic-oriented listening and speech training will be implemented in order to improve communication skills. Improve the quality of English seeing, listening, and speaking education through promoting the modernization of educational material, instructional techniques, and procedures. Increasing higher education reforms necessitate a solution to the problem of how to fairly assess the quality of English teaching, encourage the improvement of teaching objectives, and improve the quality of English teaching as a whole. Because of this, measuring the quality of English teaching has become a crucial link in the teaching management process, and researching methods or models for evaluating English teaching quality has emerged as a key study area in the direction of scientific and standardized education [1–4].

For nonlinear systems, an artificial neural network is one made of numerous computing neurons that can be configured differently among the various levels. Nonlinearity, self-organization, and self-learning, as well as large-scale parallel processing, are some of its advantages. McCulloch and Pitts were pioneers in artificial neural network research in the 1940s, proposing the mathematical model of neurons as early as that decade. The perceptron model, the back propagation algorithm, the Boltzmann machine, the unsupervised learning, and the supervised learning are only a few of the innovative theories, whereas the algorithms of artificial neural networks have been proposed since a huge number of researchers joined the research. Theory and data processing have both improved steadily. For problems that traditional methods and models cannot address, artificial neural networks have been used as a mathematic model for processing calculations with satisfactory results in practice. The scientific research team led by Rumelhart and McClelland has suggested the BP neural network as a proposal. The back propagation technique was used to train this multilayer feed-forward network. Gradient descent method is used to rectify error signals created during forward propagation until the accuracy target is satisfied or the number of iterations is completed in BP neural network. As a result of the Hecht-Nielsen result, every closed-interval continuous function can be roughly represented by an unobserved third-layer BP neural network. Because of difficulties such as poor convergence speed and easy fall into the minimum, the BP neural network is unable to deal with high-level abstract complex problems despite its powerful information processing and nonlinear mapping capabilities. There are deep learning structures like the multilayer perceptron with numerous hidden layers that may be utilized to address nonlinear issues that are far more sophisticated and abstract in nature. Layer-by-layer training based on the deep belief network was proposed by Geoffrey Hinton et al. (DBN). Multiple restricted Boltzmann machines are stacked in sequence to generate a deep structure in the method, in order to solve the optimization connected to the deep structure. A DBN is then used to solve the optimization. Because of the challenge, researchers have come up with a deep structure model of a multilayer autoencoder. The release of Geoffrey Hinton's and others' research results sparked a research boom in deep neural networks in academia and industry, resulting in a significant increase in the quantity and scale of neural network models [5–9].

On the basis of this, this study suggests an upgraded BP neural network, which combines the dragonfly algorithm and BP neural network to evaluate the quality of teaching English in universities and colleges. Using this strategy, we are able to improve our evaluator's efficiency while also improving performance.

The rest of the paper is organized as follows: Section 2 focuses on the related work, and the Section 3 revolves around the methodology. Section 4 basically throws light on DA-BP Algorithm. At last, the paper contains the final section that is conclusion along with the future work.

2. Related Work

Since the neuron mathematical model was proposed in the 1940s, many scholars have been interested. The literature first established the connection weight training algorithm now called as Hebb algorithm, which lays the foundation for neural network. Due to the fact that it was impossible to prove theoretically that the multilayer network's perceptron model was meaningful, the research on artificial neural networks entered a low point. The literature absorbs and summarizes the research results of artificial neural network structure and algorithm, proposes the Hopfield model, and proves that under certain conditions, the network can reach a stable state. The literature absorbs and summarizes the research results of artificial neural network structure and algorithm, proposes the Hopfield model, and proves that under certain conditions, the network can reach a stable state [10–14].

The research of evaluating teaching quality was began earlier than in our country by countries such as the UK, the USA, and Japan, who proposed related ideas and methods such as the theory of multiple intelligence, constructivism theory, and the Taylor assessment model. A five-point scoring system was presented and formulated in the literature for the first time. A book *Introduction to Psychological and Social Measurement* was released which served as a theoretical foundation for educational measurement standardization as well as a sign of the field's maturity. Among Russia's evaluation approaches are self-evaluation based on schools, evaluation based on the state, and self-supervised evaluation in the form of social competitions. According to the Japanese government, it is necessary to conduct a review on two tracks at the same time; therefore, a multitrack, objective, and transparent evaluation system was developed. Accurately assessing college or university teaching quality involves solving an optimization problem that has multiple levels and multiple objectives. There is a lot of substance in the evaluation, and the link between influencing elements and teaching quality is complex and nonlinear, making a mathematical model difficult to represent effectively. Teaching quality is currently assessed at colleges and universities using an evaluation index system that relies heavily on factors such as student learning outcomes (SLOs), content knowledge (content knowledge), and teaching methods (methods and models). Fuzzy comprehensive evaluation, fuzzy analytic hierarchy process, correlation analysis, ID3 algorithm, support vector machine, and BP neural network model are among the extant assessment methods and models. The research suggests that the Apriori algorithm can be improved in order to mine the teaching system's data and assess the institutions' teaching quality. Support vector machines are used to learn from and assess current classroom teaching quality evaluation data samples in the literature and other sources. To establish a training quality evaluation model based on teaching quality, the literature has used the BP neural network. This shows that the BP neural network method is highly operable and not only avoids the evaluation process' complexity but also fixes the analytic hierarchy process' shortcomings of subjectivity and randomness [15–22].

3. Methodology

3.1. BP Neural Network. As far as multilayer feed-forward neural networks go, the BP neural network is a classic. Its goal is to move the mistake from the network output layer to the network input layer in the opposite direction of the input signal transmission, layer by layer, via the hidden layer. And make sure to correct each layer's mistakes as they occur. Signal forward propagation and error back propagation are the two halves of the BP neural network's learning process. The input signal is input by the input layer and processed and calculated by each hidden layer and connection weight when traveling in the forward direction. The final outcome of the forward propagation process is the output on the output layer. When calculating the error back propagation, the error function is utilized to determine the discrepancy between the output layer's final actual value and the target expected value. It is possible that the error will propagate back and forth from the output layer via all concealed layers until it reaches the input layer, although this is unlikely. Add the error value to each layer of the network and then tweak neuron weight and threshold values for each layer based on that information. After a certain number of iterations or a final error value meets the network's target error condition, the entire learning process terminates. Figure 1 depicts the network structure.

If the input dimension and output dimension of the BP network are n and 1, then the mapping mathematical expression is

$$y = \frac{1}{1 + \exp\left(-\sum_{i=1}^{p} c_i b_i + \varepsilon\right)}. \tag{1}$$

The output of the hidden layer node is

$$y = \frac{1}{1 + \exp\left(-\sum_{i=1}^{n} w_{ij} x_i + \theta_j\right)}. \tag{2}$$

There are many factors that can influence BP neural network prediction outcomes, and it is easy to become caught up in the dilemma of local extremes. The initial connection weights and thresholds of the BP neural network are optimized using the dragonfly algorithm (DA) in this research.

3.2. Dragonfly Algorithm. The gregarious behavior of dragonflies is static and dynamic. The living behavior of these two groups is very similar to the two main stages of metaheuristic optimization: exploration and development. Dragonflies create subgroups and fly over different areas in a static group. This is the main goal of the exploration phase. However, in a dynamic situation, dragonflies flock in groups and fly to one direction, which is advantageous in the development phase.

Because of its simple structure and consistent search results, this method is frequently utilized in a variety of domains such as parameter optimization and global optimization. This method simulates a static group to search for food locally and a dynamic group to migrate in a large range. The dragonfly algorithm mainly simulates the separation, parallelism, aggregation, foraging, and avoiding enemies of dragonflies. The foraging process is the optimization work. Optimization process of dragonfly individuals is as follows: five position vectors are generated through separation (S_i), alignment (A_i), cohesion (C_i), attraction to food (F_i), and distraction from enemy (E_i). The new dragonfly's position increment is generated using the step length formula, and the transfer function is then evaluated based on the position increment to update the population.

There are five behaviors of individual dragonflies that require special attention, and these behaviors determine the position of the dragonfly during flight. (1) For collision avoidance behavior, try not to collide with surrounding or to be close to dragonflies as much as possible. (2) For the behavior of grouping, several dragonflies fly in groups, and the individuals are connected at the same average speed. (3) For gathering behavior, several dragonflies move closer to a certain dragonfly, and the individuals fly at equal intervals. (4) For foraging behavior, find food as much as possible, and move closer together to the location of the food. (5) For avoid enemy behavior, encounter natural enemies as little as possible, and spread around them. Each body in the dragonfly colony updates its position according to these five main behaviors.

These five behaviors can be abstracted as the algorithm model of dragonfly colony flying.

The S_i is

$$S_i = -\sum_{j=1}^{N} X - X_j \tag{3}$$

The A_i is

$$A_i = \frac{\sum_{j=1}^{N} V_j}{N} \tag{4}$$

The C_i is

$$C_i = \frac{\sum_{j=1}^{N} X_j}{N} - X. \tag{5}$$

The F_i is

$$F_i = X^{+} + X. \tag{6}$$

The E_i is

$$E_i = X^{-} + X \tag{7}$$

DA uses different vectors to address the problem:

$$\Delta X_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta X_t \tag{8}$$

After calculating the step length, the new individual update method is

$$X_{t+1} = X_t + \Delta X_t. \tag{9}$$

According to separation, parallelism, aggregation, predation, and avoidance factors, different forms of global and local search methods can be generated during the optimization process of the algorithm. The neighbors of dragonflies are very important in the algorithm's search process,

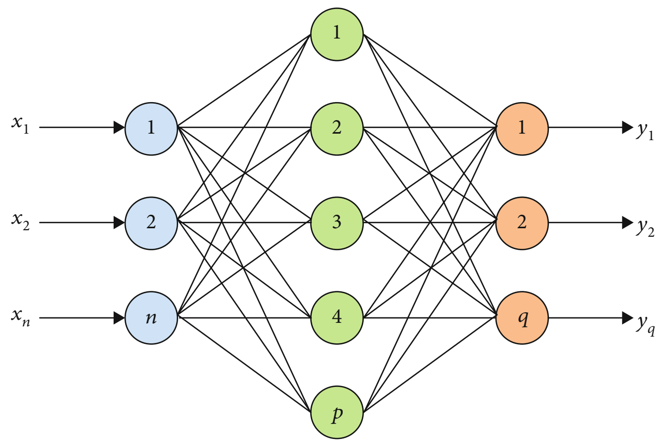

Figure 1: BP neural network.

assuming that each dragonfly has neighbors within a certain radius.

According to the previous part of the argument, the dragonfly algorithm is divided into two types of populations: static populations and dynamic populations. In a dynamic group, dragonflies maintain parallel and converging behavior by adjusting their flight direction. However, in a static population, prey is captured through low parallelism and high aggregation. It can be seen that dragonfly uses high separation weight values and low aggregation weight values to explore unknown areas and uses high aggregation and low parallelism to search in known spaces. In order to balance the relationship between exploration and development, the radius of the field can be set to increase proportionally with the number of iterations. Another way is to adjust various weighting factors in the search optimization process.

Another problem may arise here, that is, how to ensure the convergence of the dragonfly during the optimization process. Dragonflies need to adaptively change their weights to achieve the transition between development and exploration. At the same time, it is assumed that as the optimization process progresses, the dragonfly constantly adjusts its flight path during the search process to find more other dragonflies (possible solutions). In other words, by increasing the neighborhood search area, the group becomes a group in the final stage of optimization and converges to the global optimum. Food sources and natural enemies are the best and worst solutions found from the candidate subset so far. This indicates that the search space will converge to a promising area and diverge in a hopeless area.

Random walk (Levy flight) without neighbor dragonflies can increase the randomness, random behavior, and development ability of a person. The dragonfly's current location is

$$X_{i+1} = X_t + Levy(d) * X_i. \quad (10)$$

3.3. DA-BP Algorithm. Based on the DA-BP, the process of evaluating the teaching effect of college English viewing, listening, and speaking courses can be summarized as the following detailed steps.

Table 1: Teaching quality evaluation index.

Index number	Index
1	Teacher ethics
2	Teaching attitude
3	Teaching content
4	Teaching method
5	Teaching effect
6	Research ability
7	Professional extension
8	Student response

Step 1. Initialize BP network model and determine the structure. Determine the number of layers, the type of transfer function and training function, and the number of nodes in each layer according to the data samples. Read the classroom teaching quality evaluation data, perform the preprocessing, and divide the data.

Step 2. Encoding. DA algorithm uses real number coding to encode the connection weights and thresholds as a whole. The search space dimension of the algorithm is n. If the hidden layer and output layer are I, N_1, and N_2, respectively, the code length L is

$$L = IL + N_1 N_2 + N_1 + N_2. \quad (11)$$

Step 3. Initialization of DA algorithm parameters: population size N and maximum number of iterations T.

Step 4. Randomly initialize step vector ΔX; randomly generate the initial position X of dragonfly individual.

Step 5. Set the current iteration number $t = 1$, input the training set into BP, calculate the fitness of all dragonfly individuals based on the fitness function, and sort and record current optimal solution.

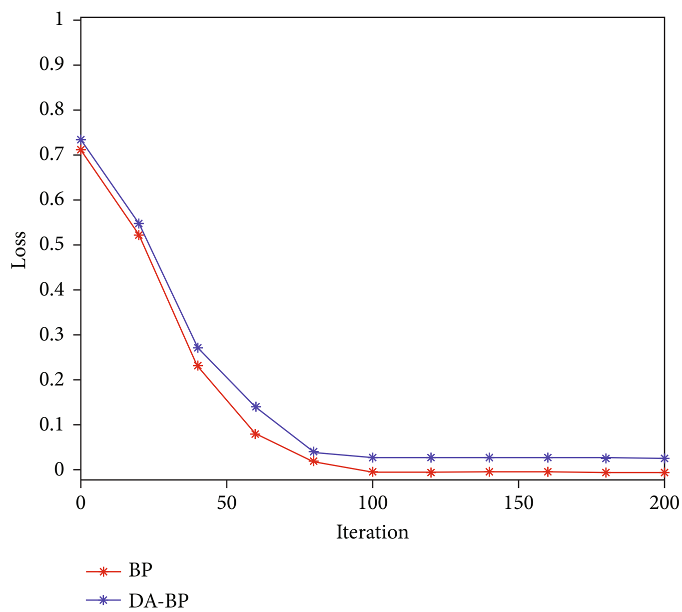

Figure 2: Training loss.

Step 6. Update the food source position, the natural enemy position, and update the 5 behavior weights and inertia weights.

Step 7. Update weights according to Equations (3)~(7).

Step 8. According to Equations (1) and (2), update the step vector and position vector.

Step 9. The optimal connection weights and the threshold are saved if the number of iterations is more than T. Otherwise, $t = t + 1$ and Step 5 are repeated.

Step 10. Make use of the optimal solution's weights and thresholds as the initial BP neural network weights and thresholds for training and making predictions.

4. DA-BP Algorithm

4.1. Evaluation Index System Design. In the construction of evaluation system of teaching effect, this paper adopts expert interviews, questionnaire surveys, and other methods, aiming at the teaching evaluation objects of different departments and different disciplines. Establish corresponding teaching effect evaluation index systems, focusing on selecting evaluation factors that have a high degree of relevance to the evaluation object. Through consultation, interviews, questionnaires, and other forms, on this basis, the initial data is sorted, qualitatively and quantitatively analyzed, and the proportion of evaluation indicators in the entire indicator system is initially formed. In the project research, the evaluation information of the teaching evaluation experts is collected in the form of face-to-face with the experts, and then the entire quality evaluation system is established by majors and disciplines. Use software to process these data to find out which of the many factors are recognized and necessary considerations. Some of the options are caused by different disciplines, and these also need to be considered. Issues such as these are what we should pay attention to when establishing a sound teacher teaching quality evaluation system. The purpose of this is to make the model as comprehensive and reasonable as possible. Combine references and teaching experience, using the analytic hierarchy process to construct the structural indicators for the evaluation of college English viewing, listening, and speaking classroom teaching effect, as shown in Table 1.

4.2. Dataset and Evaluation Metric. Select a certain engineering university English audio-visual science teaching quality data from 2018 to 2019 as the research object, including a total of 253 data. Two-thirds of them are used as the training set, and one-third are as the test set. To test the performance of the evaluation results of ideological and political classroom teaching, the evaluation index selects the root mean square error (RMSE).

4.3. Evaluation on Training Loss. Training loss can effectively evaluate whether the network has converged and how fast it is, and it plays a significant role in the performance evaluation of neural networks. Therefore, we first visualize the loss during network training. At the same time, to evaluate the impact of dragonfly algorithm on network training, compare the loss when the dragonfly algorithm is not added. The result is shown in Figure 2.

As the number of iterations increases, both networks can converge. But after adding the dragonfly algorithm, the convergence speed of the network becomes faster, and the final loss is smaller than the BP algorithm. This proves the effectiveness.

4.4. Comparison with Other Methods. To prove the effectiveness of DA-BP method, the method is compared with

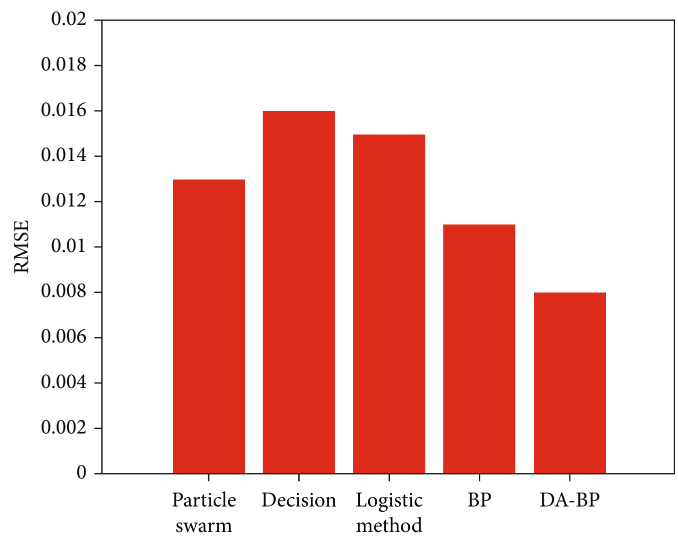

Figure 3: Comparison with other methods.

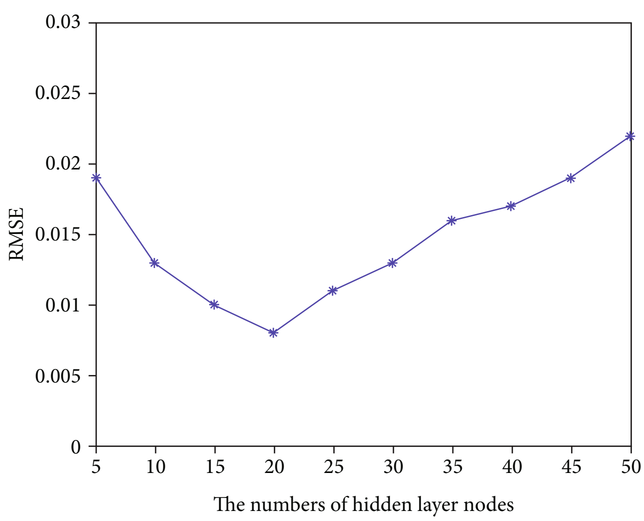

Figure 4: Evaluation on the number of hidden layer nodes.

particle swarm algorithm, decision tree algorithm, logistic algorithm, and BP algorithm. The experimental result is illustrated in Figure 3.

The RMSE obtained by our DA-BP is the smallest, which proves that our method surpasses other methods and is more suitable for the evaluation of English courses.

4.5. Evaluation on the Number of Hidden Layer Nodes. As we all know, in DA-BP and other BP neural networks, the number of nodes in the hidden layer is variable. To evaluate the impact of different numbers of nodes on the performance, this paper conducts a comparative experiment with different numbers of nodes. Experimental results are illustrated in Figure 4.

At the beginning, as the number of nodes increases, RMSE decreases. When the number of nodes is 20, the best performance can be obtained. But then, as the number of nodes further increases, network performance gradually declines.

5. Conclusion

College English viewing, listening, and speaking teaching effect evaluation is a significant part of the teaching management process of universities. There are many evaluation indicators needed, and they are affected by many factors, which make the complex nonlinear relationship between the evaluation indicators and the results of teaching effects appear. Traditional evaluation methods include analytic hierarchy process, fuzzy comprehensive evaluation, ID3 algorithm, and support vector machine, but they have problems such as too strong subjectivity and randomness, difficulty in determining index weights, prone to overfitting, and slow optimization speed. This paper introduces the dragonfly algorithm into the BP network and proposes DA-BP network for efficient evaluation of English viewing, listening, and speaking courses. The research results show that compared with the traditional artificial neural networks, DA-BP neural network proposed in our paper can effectively improve the evaluation performance of college English viewing, listening, and speaking classroom teaching quality. It provides new methods and approaches for the evaluation of college English classroom teaching quality.

5.1. Future Work. The proposed DA-BP neural network can be made functional in learning institutions. The evaluation performance can be further increased with the help of optimization. It can be really helpful in the enhancement of the three attributes related to English, i.e., viewing, listening, and speaking.

Data Availability

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

Conflicts of Interest

The author declares that he has no conflict of interest.

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