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Retraction

Retracted: Higher Education Teaching Quality Evaluation Model Based on Improved RBF Neural Network

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Peer-review manipulation

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.

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.

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[1] X. Qi, A. Tan, and Y. Gao, "Higher Education Teaching Quality Evaluation Model Based on Improved RBF Neural Network," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 5495728, 11 pages, 2022.

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Research Article

Higher Education Teaching Quality Evaluation Model Based on Improved RBF Neural Network

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In order to improve the reliability of higher education quality evaluation, this paper improves the RBF neural network algorithm based on the characteristics of higher education teaching data. Using RBF neural network technology, the predictive model established after learning from samples of actual teaching data can be used to evaluate teaching quality. Moreover, this paper combines the improved RBF neural network to construct a higher education teaching quality evaluation model. The model built in this article needs the support of a support vector machine (SVM) to build a sentiment analysis module and a teaching quality evaluation module. After the model is constructed, the performance of the model built in this article is evaluated, and the performance of the model is displayed by combing statistics. The teaching quality assessment of the higher education model is between 80% and 85%.The test results show that the higher education teaching quality appraise model depended on the improved RBF neural network put forward in this paper has certain effects.

1. Introduction

At present, basic education curriculum reform is being carried out comprehensively, extensively, and in-depth in our country. The core issue of basic education reform is curriculum reform, and the key to curriculum reform lies in classroom teaching reform. Over the years, teachers have formed accustomed teaching models, teaching methods, and teaching content, which have essentially collided with the new curriculum concepts and requirements. Therefore, how to better internalize the concept of the new curriculum into classroom teaching behaviors to make the reform goals of the new curriculum truly implemented, the key is to develop classroom teaching evaluation standards and methods consistent with the new curriculum. Therefore, based on the basic concepts advocated by the new curriculum, it is of great practical significance to scientifically and effectively determine the basic factors of the new curriculum classroom teaching evaluation [1].

As China's traditional basic education, it has its own advantages. But with the development of the times, its drawbacks have gradually emerged. For example, in classroom teaching, emphasis is placed on the imparting of knowledge, less on the cultivation of ability; on the teaching of teachers, less on the learning of students; and on the cultivation of intelligence, less on ignoring the cultivation of nonintellectual factors [2]. Because education emphasizes results and neglects process, students learn passively and lack interest and motivation in learning. Teachers turn students into containers of knowledge. In teaching, there is more rote memorization and no knowledge generation, which is a clone of knowledge. In this kind of teaching environment, the evaluation of classroom teaching focuses on "how the teacher teaches," instead of evaluating the teacher's teaching by focusing on "students' learning." With the launch of a new round of basic education curriculum reform, the new curriculum concept puts forward new requirements for teachers, especially teachers should have a new understanding of classroom teaching [3].

In teaching, teachers need to realize the transition from knowledge imparter to mathematics learning organizer, guide, and collaborator. Teachers need to have the ability to provide students with the necessary time, space, and resource for mathematics learning; teachers need to know the content of classroom teaching and the connection between student life and modern society and the development of science and technology; it is necessary to grasp the students' personal mathematical knowledge and direct experience, to guide students through the process of mathematics, to attach importance to students' learning to learn and to form correct values, and to foster students' improve spirit and fulfill skills. The class of the new mathematics curriculum should be a student-centered class; a class of activities, discussion, cooperation, and communication; a class that recognizes differences; a class of moral education; and a class of applying modern information technology. Because of the ugly second, the evaluation of teachers' classroom teaching can no longer stay in the original traditional evaluation method but should reflect the diversity, integrity, and process of evaluation and follow the principles of development, comprehensiveness, and subjectivity. It should start from the aspects of teacher's teaching behavior, student's learning performance, and teacher's basic quality. How to adapt to the body and mental development of students requires us to break through the traditional teaching evaluation model, boldly innovate, and practice boldly, with the development of students and teachers as the fundamental purpose. Especially in the implementation of new courses, there are many teaching quality indicators that reflect the new curriculum concept. How to determine these indicators more reasonably and scientifically and integrate them more scientifically is the key to realize the objective and reasonable evaluation of education quality.

According to the above content, this paper combines the improved RBF neural network to build a higher education quality appraise model, which can evaluate the quality of higher education teaching.

2. Related Work

In short, education evaluation is the process of judging the effect of education according to the educational goals and using scientific methods [4]. The essence of educational evaluation is management by objectives. It uses systematic engineering methods and modern scientific and technological methods and introduces the concept of value judgment. The key is to specify the content and standards of evaluation. The main basis for formulating evaluation content and standards is social needs. At the same time, it must follow the laws of talent training and growth and appropriately combine needs, possibilities, and benefits [5]. Under the evaluation purpose, the relevant attributes of the evaluation object are decomposed into evaluation indicators, and information is collected systematically within to the evaluation index system, and the collected information is analyzed quantitatively and qualitatively. Thus, it points out the direction for improving school education and national macro management. This is the whole process of teaching evaluation [6]. The research on the theory and method of teaching evaluation is juxtaposed with the research on the basic theory of education and the research on education development, so it has become one of the three major areas of contemporary educational scientific research and practice [7]. As a vital way of education appraise, teaching quality appraise refers to the sum of all the characteristics and characteristics of the teaching process and its effects that can be used to identify whether it meets the specified requirements. At present, self-evaluation of higher education quality is the primary condition for dynamic management and a significant promise for the realization of overall education management. It can be used as a monitor of teaching quality and can also be used as a booster to promote the self-discipline of teaching quality and school-running level, and it can also encourage school construction and development to keep pace with time [8].

There are many ways of appraise of teaching quality, among which the most common are absolute evaluation method, relative evaluation method, intraindividual difference evaluation method, analytical evaluation method, comprehensive judgment method, comment method, realistic method, and comprehensive scoring method [9]. In particular, the comprehensive scoring method is to first determine a clear evaluation target and formulate an evaluation index system with weight coefficients. According to the index system, qualitative judgment and quantitative analysis are combined to perform comprehensive scoring. At present, the comprehensive scoring method is the most widely used evaluation method in school teaching evaluation. It is especially suitable for the school running level, the school and department teaching management, the teaching quality of teachers, and the ideological and moral and behavioral performance of students, as well as the professional, laboratory, and evaluation of curriculum construction and other aspects [10].

Teaching evaluation has significant influence in the work of colleges and universities, and it has important guiding significance for teaching quality evaluation, evaluation of teachers' professional titles, and construction of teaching staff [11]. In view of the fact that teaching evaluation data belongs to a special field and has a certain degree of privacy, there is currently no public data set, and there are relatively few studies in related fields. Most of them are related to the reliability of teaching evaluation scores and other external attributes. Literature [12] correlates the results of teaching evaluation with teachers, courses, students, and other objects and then explores its inherent implicit connections. Literature [13] applies data mining methods to analyze the effectiveness of student evaluation of teaching. The literature [14] analyzes the "abnormal" scores in the teaching evaluation scores, and the literature [15] uses the K-means improved method based on cosine similarity as a measure to cluster the teaching evaluation data and then screen out outliers through frequency statistics. The literature [16] analyzes the reliability of the evaluation scores through the density-based outlier detection method. Most of the above depend on the related research of teaching appraise scores, and a small number of scholars have studied the comment sentences in the teaching evaluation data. Literature [17] proposed a topic emotion extraction algorithm based on the DEI-TM model for the evaluation of teaching data. But in general, there are still few related researches in the field of teaching evaluation data, which need to be further explored.

3. Radial Basis Function NNB on Teaching Quality Evaluation

RBF neural network is a feedforward neural network with excellent performance. RBF network can approximate any nonlinear function with arbitrary precision and has the ability of global approximation.

This paper solves the local optimal problem of BP network. RBF neural network has the best approximation and global optimization performance, and the training process is simple and fast, and there is no local optimization trouble. These merits make RBF neural network widely applied in nonlinear prediction.

If the function $h \in L^2(R^d)$ is radial, then there is a function $\Phi \in L^2(R)$. For $\forall x \in R^d$, the following formula holds [18]:

$$h(x) = \Phi(\|x\|). \tag{1}$$

Radial basis function is a scalar function that is symmetrical along the radial direction, usually defined as the radial distance between the sample and the data center. Among them, $\|x\|$ represents the Euclidean norm of x, and its Fourier transform is also radial.

$$h(x) = \Phi\left((x-c)^T E^{-1}(x-c)\right). \tag{2}$$

Among them, Φ represents the radial function, C represents the center vector of the function, and E is a transformation matrix, which is usually a Euclidean matrix. Under the conditions defined by the matrix E, $(x-c)^T E^{-1}(x-c)$ represents a measure of the gap between the input vector x and the center C.

If E represents a Euclidean matrix, in this case, $E = r^2 I$, then the above formula is simplified to

$$h(x) = \Phi\left(\frac{(x-c)^T(x-c)}{r^2}\right). \tag{3}$$

Under normal circumstances, it is further simplified as follows:

$$h(x) = \Phi\left(\frac{\|x-c\|^2}{r^2}\right). \tag{4}$$

In addition, the radial basis function also has an important feature: as the gap from a certain center point increases and the function curve shows a monotonic (increasing or decreasing) trend.

The following are several types of commonly used radial basis functions, such as the following:

The Gaussian function is

$$\Phi(x) = e^{-\|x\|^2}. \tag{5}$$

The multiquadric function is

$$\Phi(\|x\|) = \left(1 + \|x\|^2\right)^{1/2}. \tag{6}$$

Inverse multiquadric function is

$$\Phi(\|x\|) = \left(1 + \|x\|^2\right)^{1/2}. \tag{7}$$

The radial basis function is a kind of nonnegative nonlinear function with a local distribution that attenuates or enhances radially symmetrically about the center point. It has two main parameters: one is the center of the base, that is, the point of symmetry, and the other is the width of the base, that is, the range of the obvious output response in the area. Their function distribution in the two-dimensional case is shown in Figure 1, where C-0, $r = 1$.

As shown in Figure 1, the Gaussian function has a wide range of applications, and it can be seen in the fields of natural science, social science, mathematics, and engineering. It can be seen from Figure 1 that as the distance from the center point continues to increase, the inverse multiquadric function curve increases monotonically, while Gaussian and inverse multiquadric decrease monotonously.

The RBF neural network is a three-layer feedforward neural network with the radial basis function as the hidden unit's activation function. Figure 2 depicts the topological structure of the RBF neural network as defined in the definition. Self-organizing neural network, also known as self-organizing competitive neural network, is especially suitable for solving application problems in pattern classification and recognition. The network model belongs to the forward neural network model and adopts unsupervised learning algorithm.

The center of the hidden layer unit basis function is denoted by C_i, the width is denoted by σ_j, and the connection weight between the hidden layer unit and the output layer unit is denoted by W_k (j and k denote the hidden unit and the output unit, respectively), as shown in Figure 2.

As shown in Figure 2, its mathematical model can be expressed as follows.

If it is assumed that there are P learning samples in the sample set and the input mode is $X_p = (X_{p1}, X_{p2}, \cdots, X_{pn})^T$, then the output of the hidden layer unit is

$$h_p^j = \frac{R_j^p}{\sum_{j=1}^d R_j^p} (p = 1, 2j = 1, 2, m). \tag{8}$$

Among them,

$$R_j^p = \exp\left[-\sum\left(\frac{x-_i^p C_{ij}}{2\sigma_j}\right)\right]. \tag{9}$$

In the formula, R_j^p is the hidden layer radial basis function, that is, Gaussian function, and h_p^j is the normalized hidden layer radial basis function.

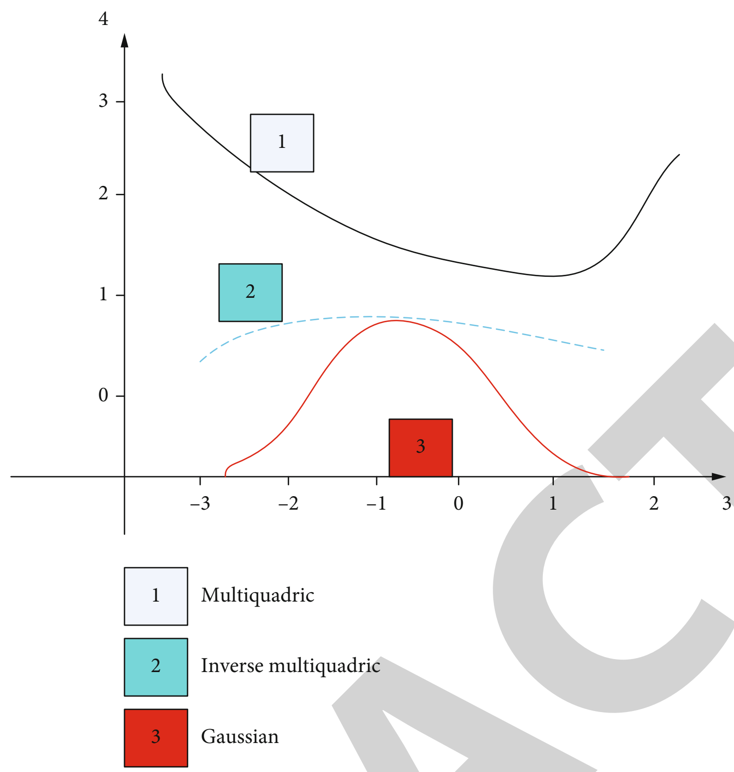


FIGURE 1: Several commonly used radial basis functions.

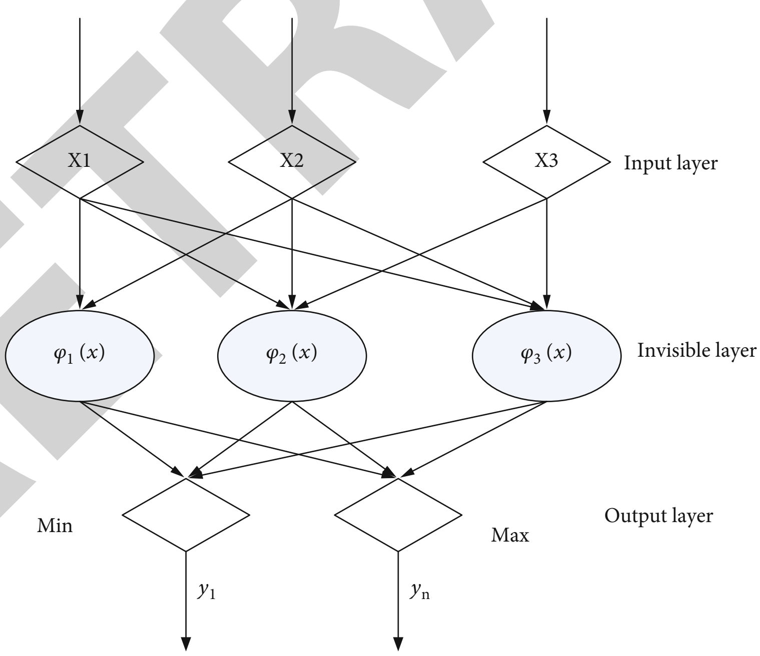


FIGURE 2: BRF network model structure diagram.

The output of the output unit is

$$y_k^p = \sum_{j=1}^{d} W_{jk} h_j^p (p = 1, 2, p\, k = 1, 2, l). \tag{10}$$

The basic idea of RBF neural network uses RBF as the "base" of the hidden unit to form the hidden layer space; the hidden layer transforms the input vector and transforms the low-dimensional pattern input data into the high-dimensional space, so that in the low-dimensional space, linearly inseparable problems are linearly separable in high-dimensional spaces. The radial basis function (RBF) neural network is a three-layer feedforward neural network, and its hidden layer and output layer have different functions. The RBF neural network is used to approximate the nonlinear system. After the learning sample data is given, the algorithm mainly solves two problems:

(1) Neural network structure design issues include the determination of the number of nodes in the covert layer of the network and the determination of the clustering center C of the RBF

(2) The weight correction problem is to adjust the connection weight matrix W from the hidden layer space to the output layer space

The hidden layer of the RBF network is to adjust the parameters of the RBF, using a nonlinear optimization method. However, the output layer adjusts the linear weight matrix and uses a linear optimization method. Therefore, their learning algorithms are also different. Correspondingly, the learning algorithm of the RBF neural network can be divided into two parts: weight adjustment and center determination, and the two can be performed synchronously or asynchronously. It should be determined according to the complexity of the specific problem and the specific problem that needs to be solved.

In the RBF network, the effect of the neural network is greatly affected by the RBF center. If the center is selected improperly, the performance of the RBF neural network constructed generally cannot meet the requirements. For example, when the distance between certain centers is too close, it will produce an approximately linear correlation artifact, causing numerical lesions. Therefore, there is a reasonable choice, and try to optimize the network structure to make the number of hidden layer units as few as possible is the main purpose of determining the RBF center.

At present, the commonly used methods for determining the center are as follows:

(1) Randomly select the RBF center (direct calculation method). This is the simplest way to determine the center. However, in most cases, the number of input samples has a certain degree of redundancy, and this kind of center selection algorithm is obviously powerless

(2) The self-organizing learning algorithm selects the RBF center. In this algorithm, the center of the RBF neural network determines its specific location through self-organizing learning. The purpose of self-organizing learning is to make the center of the RBF neural network at an important position in the input space, so that the selected center forms a specific distribution form determined by the sample data. It characterizes the inherent characteristics of the input sample vector space. In a sense, it redistributes network resources

(3) Select RBF center for supervised learning. In this algorithm, the RBF center is determined through supervised learning. It is usually determined by nonlinear optimization methods such as gradient descent method and conjugate gradient method. Orthogonal regression orthogonal polynomial regression is an effective statistical method though

(4) Orthogonal regression method selects RBF centers. This is an important RBF neural network learning algorithm. The RBF center is appropriately selected from the sample data according to certain learning rules. During the learning process, the number of hidden layer units is dynamically adjusted, and during the learning process, it can be ensured that the learning error is not greater than the given error value

(5) Use the evolutionary optimization algorithm to select the RBF network center. This method uses the evolution strategy to perform a multipoint random search on the selected path in the solution space and find the optimal path. Due to the randomness of the evolution strategy, all selection paths have the possibility of being searched, which makes it possible to find the global optimal solution of the network

The error function is a sum of squares function, which is also used in neural networks. The sum of square error function is considered:

$$E=\sum_{p=1}^{s} E_p=\frac{1}{2}\sum_{p=1}^{s}\left[\hat{y}(X_p)-y(X_p)\right]^2, \tag{11}$$

$$w_{ik}=-\eta\frac{\partial E}{\partial w_{ik}}=-\eta\sum_{p=1}^{s}\frac{\partial E}{\partial w_{ik}}=-\eta\sum_{p=1}^{s}\frac{\partial E}{\partial \hat{y}(X_p)}\cdot\frac{\partial \hat{y}(X_p)}{\partial w_{ik}}. \tag{12}$$

$(0<\eta<1)$, η is learning rate. According to formulas (9) and (11), the adjustment amount of each step of the weight w can be finally obtained:

$$w_{ik}=-\eta\frac{\partial E}{\partial w_{ik}}=-\eta\sum_{p=1}^{s}\left(\hat{y}(X_p)-y(X_p)\right)\cdot\exp\frac{\left[-\|X-C_i\|^2\right]}{(2\delta_i)^2}. \tag{13}$$

The weight correction formula is

$$w_{ik}\longleftarrow w_{ik}+w_{ik}, i=1,2\cdots,M\,; K=1,2,\cdots,N_h. \tag{14}$$

When applying RBF neural network, different learning algorithms can be used. The commonly used are error correction algorithm based on gradient descent, learning algorithm based on nearest neighbor clustering, and so on.

The following is the procedure for the most close neighbor clustering learning algorithm.

(1) The algorithm selects a suitable Gaussian function width as r and defines a vector $A(p)$ to store the sum of various output vectors. The algorithm defines

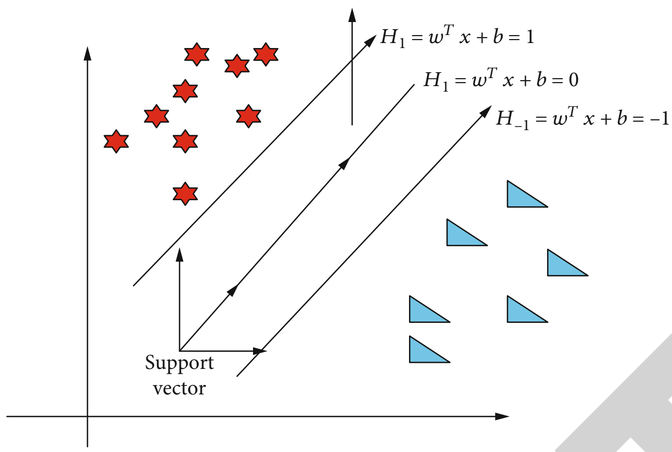


FIGURE 3: The optimal classification surface in SVM.

a counter $B(p)$ to count the number of samples belonging to every category, where p is the categories

(2) Starting from the first data pair (x^1, y^1), the algorithm establishes a cluster center on x^1. The RBF network established in this way

The output of the RBF neural network built upon the above rules should be

$$f\left(x^k\right) = \frac{\sum_{i=1}^{M} W_{l\varphi}\left(\left\|X^k - C_i\right\|\right)}{\sum_{i=1}^{M} \varphi\left(\left\|X^k - C_i\right\|\right)}. \tag{15}$$

Moreover, the greater the number of clusters obtained, the greater the amount of calculation and the higher the accuracy.

Since r is a one-dimensional parameter, in the specific operation process, it is usually only necessary to adjust the width r according to the information of the error size to complete the learning task of the network. In addition, since each input and output data group may generate a new cluster, this dynamic adaptive RBF network structure is actually a suitable adjustment to the two processes of parameters and structure at the same time.

4. Higher Education Teaching Quality Evaluation Model Based on Improved RBF Neural Network

This article combines the improved RBF neural network to construct a higher education teaching quality evaluation model, as shown in Figure 3.

As shown in Figure 3, a recurrent neural network is an artificial neural network in which nodes are oriented and connected in a loop. The internal state of such a network can exhibit dynamic timing behavior. Unlike feedforward neural networks, RNNs can use their internal memory to process input sequences of arbitrary timing, which makes it easier to handle unsegmented handwriting recognition, speech recognition, etc. The basic structure of RNN is composed of many RNN cells, each of which is used as an independent unit for time-scale information processing. This unit receives the input information from the previous moment and the output information from the previous processing unit at the same time. In this way, the output information processed by each RNN cell retains all the sequence information before that moment. The specific structure is shown in Figure 4.

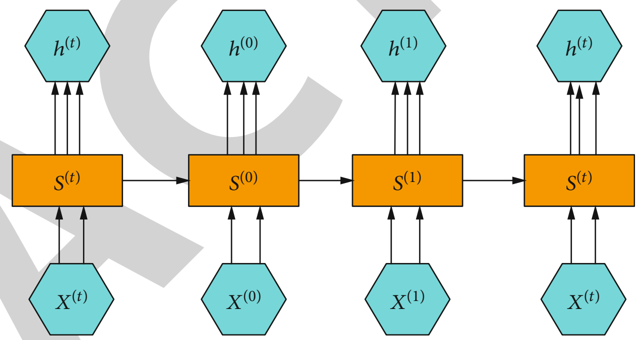


FIGURE 4: RNN expanded structure.

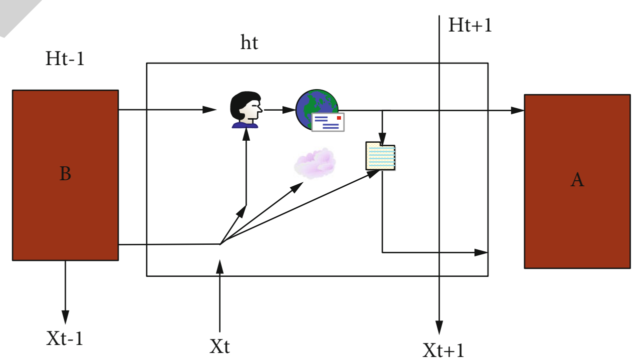


FIGURE 5: The structure of each cell in LSTM.

As shown in Figure 4, LSTM improves the tanh layer structure on the basis of RNN and introduces three gate operations with sigmoid activation function in each cell, namely, forget gate, input gate, and output gate. The specific structure of each cell is shown in the figure: $S^{(0)}$.

As shown in Figure 5, the general structure of TextCNN usually only contains a layer of convolution to obtain the

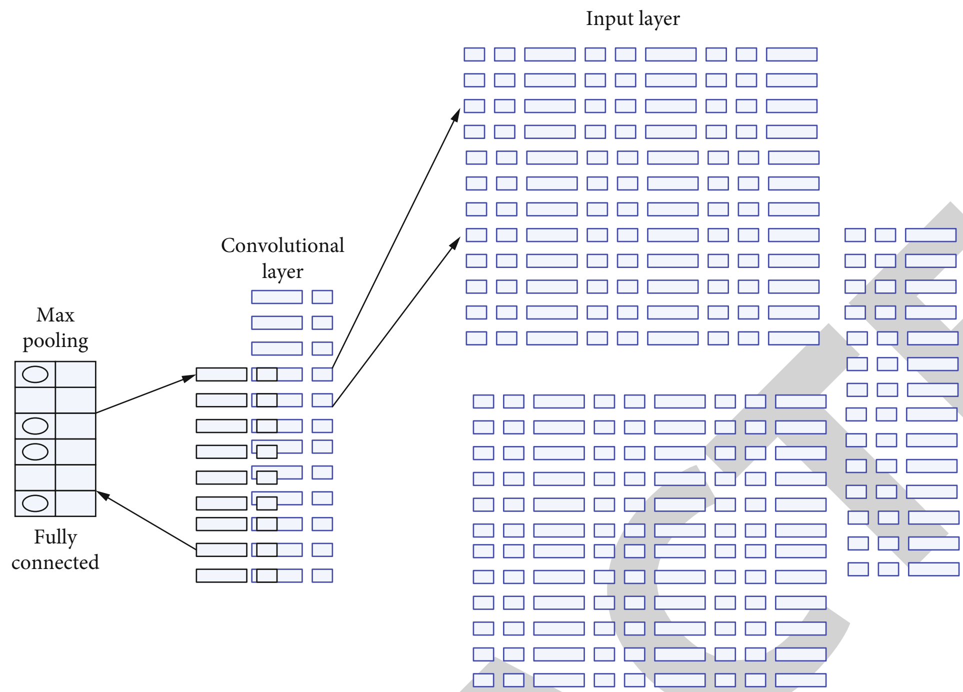


Figure 6: TextCNN model.

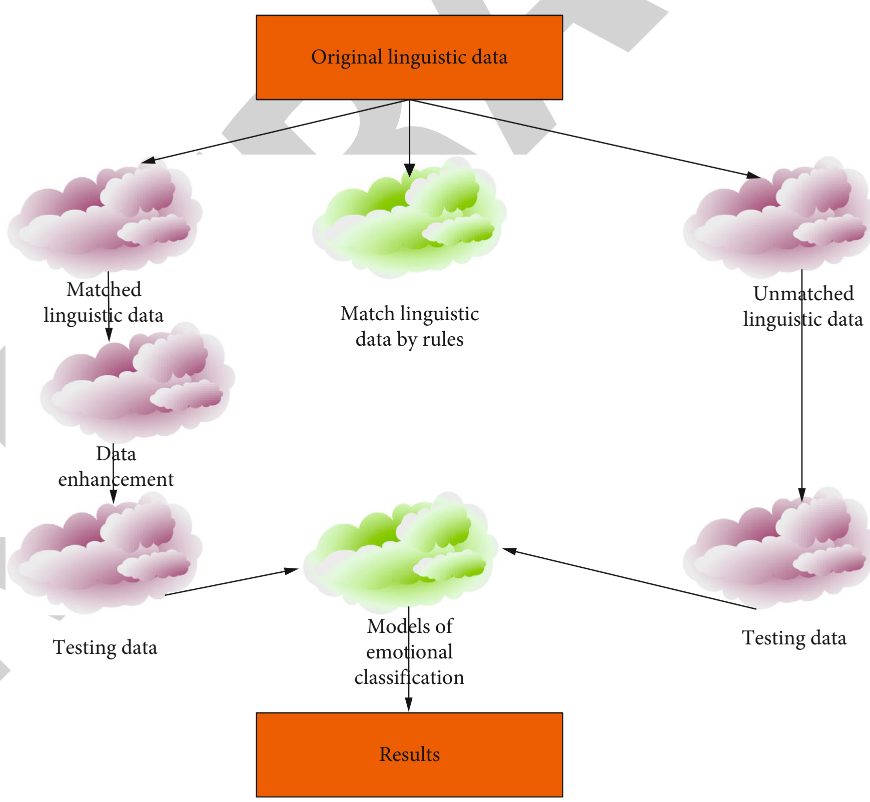


Figure 7: Sentiment classification framework based on sentiment dictionary combined with neural network.

feature representation of the n-gram in the sentence, and a layer of max-pooling is used to downsample the features extracted by the convolution layer to further compress and filter the features. Finally, the output is connected to a fully connected layer. The specific structure of TextCNN is shown in Figure 6.

As shown in Figure 6, TextCNN has more excellent performance on text classification problems. Intuitively,

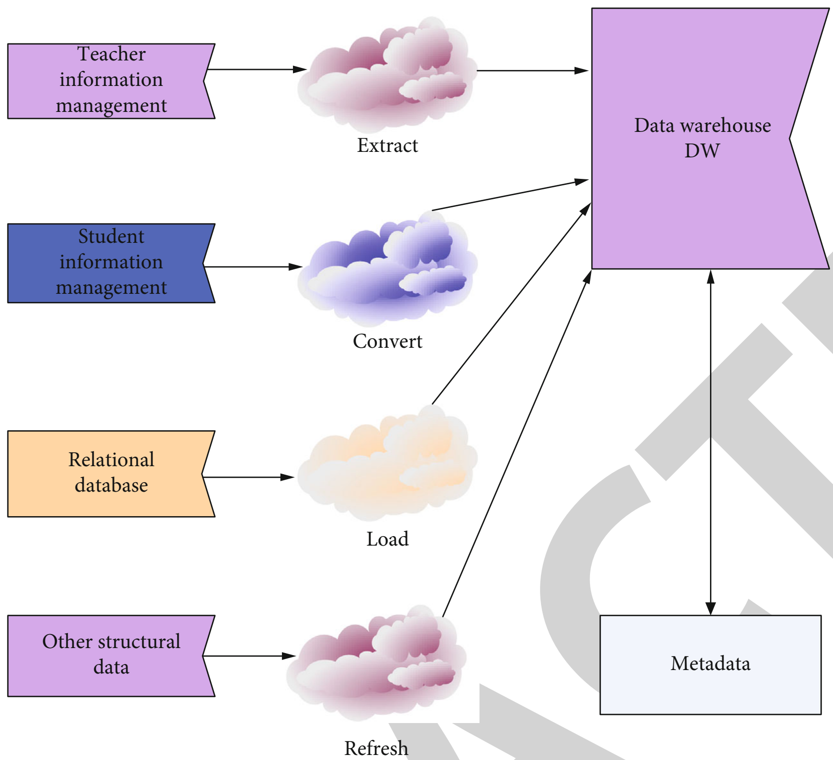


FIGURE 8: Higher education teaching quality analysis and evaluation system based on improved RBF neural network.

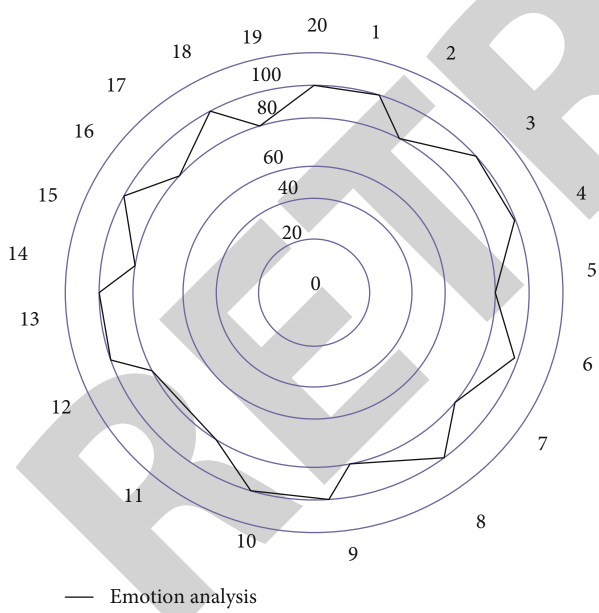


FIGURE 9: Emotional analysis effect of higher education model.

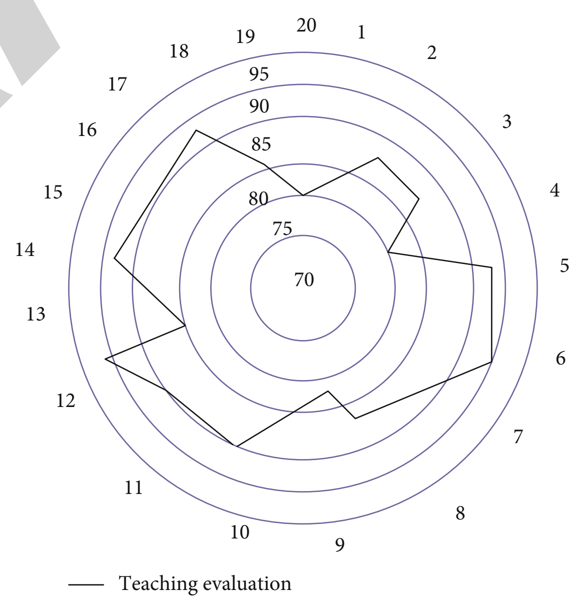
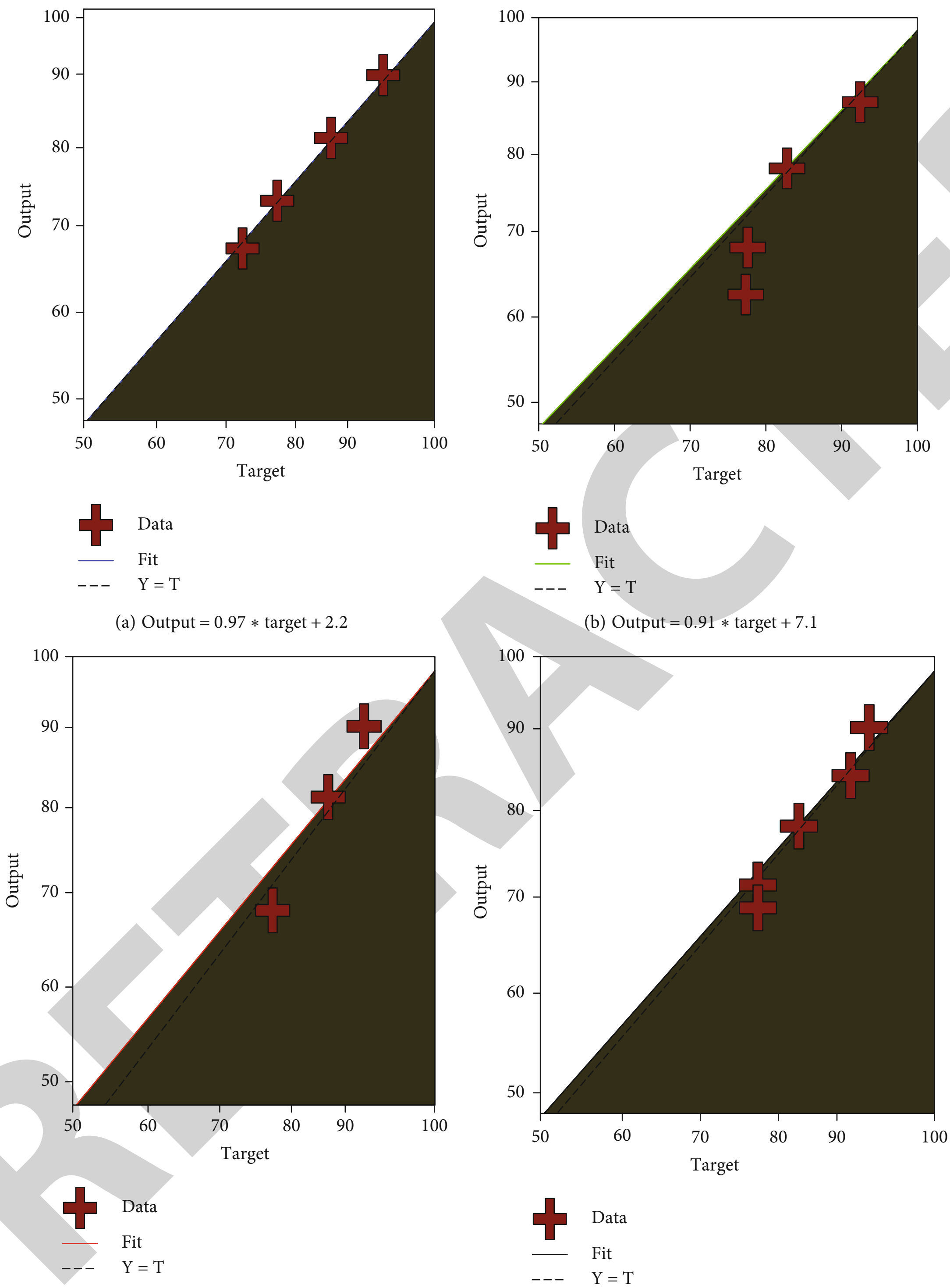


FIGURE 10: Teaching quality evaluation effect of higher education model.

TextCNN obtains the feature representation of n-grams in sentences through one-dimensional convolution. TextCNN has a strong ability to extract shallow text features, and it has a good effect in short text fields such as search and dialogue fields when it focuses on intent classification. It is widely used and fast. The teaching evaluation scores in the teaching evaluation data can be used to analyze the degree of satisfaction of students with the teacher in charge. However, in reality, many students do not strictly follow the evaluation criteria for scoring due to coping or retaliation. This has greatly affected the reliability of the evaluation scores. The comment sentence is filled out spontaneously by the students, which is more reliable. By analyzing the emotional polarity of the comment sentences, it can assist in analyzing the students' satisfaction with the teacher, in view of the characteristics of the comment sentences.



(a) Output = 0.97 ∗ target + 2.2

(b) Output = 0.91 ∗ target + 7.1

(c) Output = 0.87 ∗ target + 11

(d) Output = 0.95 ∗ target + 4.4

Figure 11: Comparison analysis results of neural network fitting regression.

Through sentiment analysis, the comment sentences with the color of “suggestion” can also be selected and analyzed separately, which is of great significance to assisting teaching. This article has developed a sentiment classification framework as shown in Figure 7.

As shown in Figure 7, under the needs of the demand analysis technique, the overall structure of the higher education quality appraise system that depends on the improved RBF neural network can be seen in Figure 7.

As shown in Figure 8, after constructing the system structure, the effect of the system is evaluated, and the sentiment analysis and education quality evaluation effects of the system are mainly studied. The results are concluded in Figures 9 and 10.

As shown in Figures 9 and 10, the higher education quality appraise model based on upgraded RBF neural network suggested in this study has certain effects, may play a good evaluation role in modern higher education, and has a certain promotion effect on enhancing teaching quality, as can be observed from the above test results.

BP is a multilayer feedforward network trained by the error back propagation algorithm, and it is one of the most widely used neural network models. According to the parameters and training results of the BP neural network model, it shows that the training proceed and verification process of the BP neural network and the overall test effect are relatively ideal, according to the analysis in Figure 11.

As shown in Figure 1, the better the fitting effect of the neural network model, the more it can show that the experimental data and model have certain regularity and rationality. The regression comparison analysis graph by neural network fitting also further verifies the accuracy of the experiment.

5. Conclusion

The evaluation of classroom teaching involves various factors. When evaluating the quality of classroom teaching, of course, the more factors to consider, the better. However, when there are more factors, it is more difficult to evaluate. At present, the methods for determining evaluation factors are mostly based on the purpose of evaluation and are determined based on subjective practical experience under the guidance of the principles of evaluation's orientation, objectivity, scientificity, validity, and feasibility. The most common ones are educational attitude, educational content, educational way, and educational result. Among the indicators determined by subjective practical experience, there are often primary, secondary, essential, and nonessential indicators coexisting at the same time. It is inevitable that there are crossover, overlap, tolerance, contradictions, and causality among various indicators. Therefore, it is required to analyze the preliminary indicators and then classify, merge, filter, and demonstrate them. This paper combines the improved RBF neural network to build a higher education quality evaluation model, which can be used to appraise the quality of higher education.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there is no conflict of interest with any financial organizations regarding the material reported in this manuscript.

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